

**The Roles of Collaborative Professional Development, Self-Efficacy, and Positive Affect in  
Encouraging Teacher Data Use in the Classroom**

By

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**The Roles of Collaborative Professional Development, Self-Efficacy, and Positive Affect in Encouraging Teacher Data Use in the Classroom**

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## Abstract

This dissertation tests a hypothesized model that links collaborative data use professional development experiences and successful use of student data in the classroom. More and more, teachers are expected to be data literate by using student data in all its forms to make effective instructional classroom strategies. Professional development providers have addressed this change by offering experiences that explore and explain effective use of student data. Specifically, this dissertation details the importance of teachers using student data in the classroom, the hallmarks of teacher professional development, the importance of teacher collaboration in professional development experiences, collaboration's link with teacher self-efficacy, self-efficacy's contribution to positive affective states related to using data, and finally, positive affect's role in engendering teacher's adoption of student data in their classrooms. A serial, regression-based mediation model is hypothesized and tested.

Survey data from over 200 K-12 educators from across the United States were collected; the sample reflected a purposeful quota based on age and gender. The survey addressed the hallmarks of effective professional development as control variables, experience in a collaborative professional development program, self-efficacy related to using data, positive affect related to using data, three operationalizations of use of student data, and finally, demographic characteristics.

If the control variables were excluded from the analyses, the hypothesized model was supported. However, when the control variables were included, collaboration no longer factored into the model significantly. Two of the control variables, active learning and focused content, seemed to have a suppressing effect on collaboration, indicating they may moderate the relationship. Two interaction variables were calculated (collaboration \* active learning, and

collaboration \* focused content) and included in the model separately. The analyses suggested both variables did moderate the relationship, in that high levels of collaboration, active learning, and focused content needed to be present in order to facilitate the relationship. However, when the interaction variables are included in the model, they affect the mediating variables separately and not in sequence. Thus, the model degrades into a parallel mediation model; serial mediation no longer seems to be occurring.

In all, the analyses demonstrate the importance of collaborative learning in professional development experiences related to use of student data. However, it seems collaboration works best when an experience is also highly focused on classroom data use (and not other content) and that it contains frequent opportunities for active learning. Professional development providers can use this knowledge to design more effective experiences. Similarly, school leaders and teacher coaches can use this knowledge to guide teachers to experiences that are likely to result in teachers developing data use skills to aid in their classroom instruction.

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## **Research Topic Interest**

In fall 2015, just after I started the Ph.D. program in Curriculum & Teaching at the University of Kansas, I was speaking with one of my best friends, Will Krebs, about my research interests. Will has served in various prestigious roles in the education industry since 2007, including being a Teach for America teacher in a rural and impoverished community, an aide and eventual deputy commissioner in the Division of Accountability, Research, and Measurement for the Florida Department of Education, and most recently, a senior vice president of Policy and Government Relations for the education non-profit Project Lead the Way. Will is entrenched at multifarious levels in the education industry; given his experience, when he gives advice, I will always listen to him.

During the aforementioned conversation, I told him I was planning on studying high school and college student statistics knowledge acquisition. He did not discount my interests; however, he did provide me with a kernel of wisdom. “J.J.,” Will said, “As part of federal and state law mandates, teachers are being forced to act as data analysts more and more, even though they aren’t receiving the proper training and support. Why don’t you think about studying that for your dissertation?”

I’d never even thought about teacher professional development related to data use as a research topic of inquiry before Will made that statement. It only took me a week to review a fraction of the literature on the topic to determine that, yes, this was an area ripe for inquiry. Over the following two years after that conversation, I explored, read, and studied a copious body of literature that made me realize I could use my dissertation to develop an effective professional development program outline that could launch an educational consultancy business.

Thanks to Will for sparking my interest, and the excellent professors in the C&T program, I was able to develop my dissertation research idea from a small thought into a fully formed project. I believe this research project will be the unofficial launch of my educational consultancy business – a company whose goal is to develop teacher data literacy and data driven decision-making.

# **The Roles of Collaborative Professional Development, Self-Efficacy, and Positive Affect in Encouraging Teacher Data Use in the Classroom**

## **Chapter 1: Introduction**

### **Purpose of the Study**

Now more than ever in the history of the profession, it is required for teachers to be data literate to improve student learning (Mandinach & Gummer, 2016). For better or worse, state and federal guidelines suggest that effective use of data in the classroom helps students learn, and keep teachers, schools, and school leaders accountable. Teachers must measure student progress across time, collecting and analyzing data from a multitude of quantitative and qualitative measures (assessments, portfolios, class activities, attendance, behavior, affect, etc.). Indeed, effective use of student data to inform a teacher's classroom decision-making abilities has been well documented in the literature across the years – data use is strongly and positively related with various student achievement outcomes (Dunn, Airola, Lo, & Garrison, 2012; Edmonds, 1979; Evans, 2009; Fuller & Johnson, 2001; Scheurich & Skrla, 2003; Stringfield, 1994; Wayman, Midgley, & Stringfield, 2006; Weber, 1971). If a student's progress stalls, the adept, data literate teacher must at once identify the problem and create a specialized intervention, which is also tracked and measured, to ensure the student continues his or her path towards growth (Farley-Ripple & Buttram, 2015).

Effective data use in the classroom is not limited to analyzing assessment scores across time. Many types of data, both quantitative and qualitative, ought to be used for a teacher to make an informed data driven decision. Per Mandinach and Gummer (2016), there are at least 13 classes of student data sources that ought to be collected, analyzed, and tracked. Broadly, these data classes are: 1) assessments, 2) classroom activities, 3) portfolios, 4) observations, 5) student

questions / answers, 6) attendance issues, 7) behavioral observations, 8) health and lifestyle observations, 9) student special statuses, 10) transportation abilities, 11) demographics, 12) home circumstances, and 13) student affective states (Mandinach & Gummer, 2016).

Certainly, developing this level of data use and analysis capacity may be daunting for a teacher. After all, teachers are humans with outside lives, interests, and families; additionally, they are still required to teach the school, district, and state curricula. This capacity to use data to inform classroom decisions is referred to as data literacy. More specifically, this is:

... the ability of instructional leaders and teachers to work individually and collectively to examine outcomes, trends, performance, and other indicators based on achievement data, formative assessment measures of student performance, students' work products, and other forms of data (e.g., demographic, affective, process, attitudes, behavioral), and to develop strategies for improvement based on these data... (Mandinach & Gummer, 2016, p. 11).

Developing sufficient data literacy is time consuming and requires durative training, and in its absence, teachers may be prone to making surface level conclusions from the data's stories. This can result in improper decision-making and faulty student intervention programs, which hinder learning rather than help it (Mandinach & Gummer, 2016).

Given the onerous but important role data driven decision-making plays in the classroom, professional development programs have been cropping up across the United States (and elsewhere) to develop data literacy skills within educators. Indeed, "Practitioners must be trained to use data, especially to understand how to translate data into actionable instructional practice," (Mandinach & Gummer, 2016, p. 11). Broadly, professional development is defined as a sustained program with the intention of growing teachers' practitioner skills, knowledge, and



attitudes to improve student learning (Guskey, 2000). Desimone (2009) defined professional development using more holistic language. “Teachers experience a vast range of activities and interactions that may increase their knowledge and skills and improve their teaching practice, as well as contribute to their personal, social, and emotional growth as teachers,” (p. 182). In short, professional development is any activity in which a teacher engages that, hopefully, results in increased educational skillsets and abilities that in turn contribute to enhanced student learning and development.

The purpose of this study, then, is to understand the necessary conditions that facilitate the relationship between collaborative professional development experiences related to classroom data use and actualized effective use of student data in the classroom to make data driven decisions. Another important element of this research is to understand the psychological pathways that link these two concepts. Understanding these pathways helps professional development providers design experiences that purposively trigger the links to convey the material effectively to teachers. This study tests a hypothesized pathway linking a data use collaborative experience and classroom data use, by way of teachers’ data use self-efficacy beliefs and positive affect related to data use, in sequence.

### **Context of the Study**

Professional development experiences are not built equally. Likewise, what constitutes a professional development experience differs by topic, content, and context. This part of the dissertation will discuss the contextual definitions of effective professional development. First, different researchers have proposed different models that explain why professional development works. According to Guskey (2002), teachers who engage in professional development are more likely than are their counterparts to change their classroom teaching practices. This leads to

increased students learning outcomes, resulting in a significant change in the teachers' attitudes and beliefs about teaching and student learning. Another team suggested a similar but more straightforward model – professional development leads to increased teacher knowledge and skills, which enhances classroom teaching practices. When classroom teaching improves, students will exhibit higher achievement levels (Yoon, Duncan, Lee, Scarloss, & Shapley, 2007). Whatever the proposed model, the story is clear; professional development has the ability to improve teachers' skills, which subsequently improves students' learning.

While the assumption that professional development improves student learning may seem safe, that conclusion may not always be correct. Not all professional development is equal in its effects. Historically, professional development has been built around the lecture format, where teachers listen to a speech from an expert for an hour or so. This format has been largely considered ineffective by modern day standards (Guskey, 2000; 2002). Fortunately, a significant body of research exists on what makes professional development effective.

One study elucidated several hallmarks of effective professional development. Before explaining these hallmarks, this groundbreaking study will first be detailed. Garet, Porter, Desimone, Birman, and Yoon (2001) convened a national probability sample of 1,027 K-12 math and science teachers from across the United States to learn what works in making professional development effective. Utilizing an expansive survey (many items of which were used in this dissertation's research) to reach out to teachers engaged in the Eisenhower Professional Development Program (a federally enacted professional development program geared towards STEMs educators), a series of professional development themes were demonstrated quantitatively to improve teacher practices. These themes were 1) Duration, 2) Collective

Participation, 3) Active Learning, 4) Content Knowledge Focus, and 5) Coherence (Garet, Porter, Desimone, Birman, & Yoon, 2001), all of which will be discussed in more detail.

The first necessary element of good professional development is it is content focused (Desimone, 2009). This refers to specific, directed content knowledge that is disseminated via an experience. For example, a professional development experience that discusses, superficially, many different teaching models would not be considered content focused. However, if the focus of the material was on just one teaching model, like project-based learning, and teachers experienced that type of model firsthand, then the professional development would be deemed content focused. According to Birman, Desimone, Porter, and Garet (2000), “If teachers are expected to teach to new standards, including complex thinking skills, it is essential that they have sophisticated understanding of the content and how students learn the content,” (p. 30). Thus, the more specific and focused the content of a professional development experience, the better the program (Desimone, 2009).

Active learning is also a hallmark of effective professional development (Desimone, 2009). Many times, professional development has been characterized as a boring lecture, where some expert talks about the content and clicks through an unengaging slideshow. Active learning, conversely, requires teachers to interact with the material firsthand. One example of this would be a teacher watching a demonstration, modeling and practicing that demonstration in a real setting, and then receiving constructive feedback via an expert or colleague (Desimone, 2009). Another example of active learning is teachers engaging in focused conversations with their fellow participants (Lieberman, 1995).

Coherence, or the degree to which the content is aligned with a teacher’s existing skills and beliefs, is another hallmark of effective professional development. In other words,

Coherence indicates the extent to which professional development experiences are part of an integrated program of teacher learning – activities that are consistent with teacher goals, build on earlier activities, are followed by additional activities, and involve teachers in discussing their experiences with other teachers and administrators in the school (Birman, Desimone, Porter, & Garet, 2000, p. 31).

Without coherence in a professional development experience, teachers are likely to determine the professional development worthless and thus, disengage.

Duration is another important aspect of a good professional development experience (Garet, Porter, Desimone, Birman, & Yoon, 2001). Duration is comprised of two elements: 1) the span of time in which a teacher is engaging in the experience, and 2) the number of hours spent in the program (Fullan, 1993; Supovitz & Turner, 2000). Desimone (2009) noted that research has yet to identify the magic number of hours or span of time needed for the duration to be considered sufficient. However, she suggested that at a minimum, an experience ought to occur over the course of one semester, and include at least 20 hours (Desimone, 2009). After all, the more time someone studies a new skill, the higher the likelihood that material is learned and deployed.

Next, a professional development experience is more likely to be good when participation is collective; that is, the teachers are homogenous to some extent. Teachers should come from the same grade, subject, department, or specialty (Birman, Desimone, Porter, & Garet, 2000). This allows for teachers to learn from and assist one another, given they are coming from similar backgrounds. Moreover, if the groups are somewhat homogenous, they will all start at roughly the same level and discuss / explore the material from a unified perspective (Little, 1993). Various studies using quantitative and qualitative methods have demonstrated when the

professional development includes collective participation, it tends to be effective (Sumerville & Johnson, 2006; Fry, 2006; Henderson, 2007; Surette & Johnson, 2015).

Finally, and of most interest to this dissertation, effective professional development is one where peer collaboration and cooperation exists. While collaboration was not identified as a hallmark by Desimone and colleagues (Birman, Desimone, Porter, & Garet, 2000; Desimone, 2009), other researchers have indicated it is an important element of effective professional development. Collaborative professional development researcher Glatthorn (1987) largely based his assertions on personal experience, professional dialogue, and interviews with fellow teachers. His scholarship is derived from qualitative data and historical analyses; however, his conclusions and recommendations have innovated hundreds of quantitative and qualitative research published in the years since his seminal essay. Indeed, according to Google Scholar, as of February 26, 2018, at least 244 more contemporary researchers have cited his work.

According to Glatthorn (1987), “Cooperative professional development is a process by which small teams of teachers work together, using a variety of methods and structures, for their own professional growth ... The definitive characteristic is cooperation among peers...” (p. 31). Why this element is so important has been well researched. Deutsch (1973) wrote that collaborative experiences are inherently rewarding, and they engender efficient communication, friendliness, and helpfulness among group members. These positive situational characteristics lead people to be solutions-oriented, resulting in task success (Stanne, Johnson, & Johnson, 1999). Examples of collaborative professional development activities are group dialogues, peer coaching, peer supervision, action research, and curriculum design teams (Glatthorn, 1987).

It should be noted these five hallmarks are not the only conditions that contribute to determining if a professional development experience was effective. Indeed, Kedzior and Fifield

(2004) have identified several other elements, including the content must be part of a teacher's daily work, it is inquiry-based, and it is integrated with curriculum and standards. Glickman, Gordon, & Ross-Gordon (2001) even identified at least 10 additional elements of effective professional development practices. Regardless, the aforementioned six elements tend to be the primary hallmarks of effective professional development discussed in the literature.

While there may be at least six hallmarks of an effective professional development program, currently, very little is understood about the mechanisms that drive the relationship between a program, teacher learning, and teacher classroom practice. That is, the research is relatively scant on explaining the psychological pathways that link effective professional development and a teacher's use of a new skill in his or her classroom. In their seminal study, Garet, Porter, Desimone, Birman, and Yoon (2001) sought to test a hypothesized model that explained the relationship between a professional development experience and a change in a teacher's practice. However, their model did not address the psychological pathways linking professional development and classroom practice; rather, they tested five of the six aforementioned hallmarks of an effective professional development experience. While their sample of over 1,000 math and science educators from across the United States allowed for robust statistical testing, the researchers merely demonstrated that coherence, duration, collective participation, active knowledge, and a focus on content knowledge, were all positively interrelated with one another; no explanation was provided that detailed why these factors led to increased teacher learning (Garet, Porter, Desimone, Birman, & Yoon, 2001). Moreover, their statistical testing procedures relied on techniques that are now considered outdated (Hayes, 2013, 2018).

## Significance of the Study

Despite a call to action for researchers to formally test the mediating mechanisms that link professional development and classroom practice (Wayne, Yoon, Zhu, Cronen, & Garet, 2008), it seems this methodological request has not been heeded by contemporary researchers. It is not enough simply to demonstrate a main effect between a teacher's involvement in a high quality professional development experience and his or her subsequent change in classroom practice. It is imperative researchers understand why this phenomenon occurs for professional development providers to design a stronger, more impactful experience for teachers. After all, if we understand why this phenomenon occurs, professional development providers will be able to embed elements in the experience that manipulate and heighten the participants' interest in the topic, hopefully resulting in the greatest possible amount of change in their classroom practices.

The value of this study is three-fold. Firstly, this dissertation will formally test a mediated model linking experience in a highly collaborative professional development program and teacher classroom practice as a result of the program; recall that a professional development experience that is highly collaborative tends to be more effective compared to a less collaborative experience (Glatthorn, 1987). Secondly, not all collaborative efforts are the same; this dissertation will delve into different conceptualizations and operationalizations of the various types of collaborative experiences within a professional development program to learn which type(s) lends itself to increased teacher data use. Finally, this dissertation will situate this hypothesized model in the realm of a professional development experience related to data driven decision-making and teachers' subsequent abilities to use student data to make informed classroom decisions. Again, given the importance of teachers to be able to use data in their classrooms to make decisions (Mandinach & Gummer, 2016), it is imperative professional

development providers design the most efficacious and engaging content that properly conveys this important material. In short, it is hypothesized that engagement in a highly collaborative professional development program focusing on classroom data use will lead to increased levels of teacher self-efficacy regarding their ability to use data in their classroom, which will then lead to increased levels of positive affect related data use. This, in turn, will result in a teacher's successful use of data in the classroom.

### **Assumptions**

This research relies on several assumptions. First, the concept of teacher professional development is somewhat broad in scope, as previously described. That is, a professional development experience can 1) be a traditional lecture where an expert discusses a concept of importance, 2) be an engaged action research project where a team of teachers works in tandem to practice a skill or delivery mechanism, or 3) a collaborative professional learning community meeting, among many others. It is assumed that teachers share the multifaceted belief in what constitutes a professional development experience. It is plausible that some teachers very narrowly conceptualize professional development whereas others share a broader understanding of the concept. Regardless, this dissertation takes the broad perspective, which was defined in the previous section.

This dissertation also relied on a survey methodology to collect data related to its research questions and hypotheses. It is assumed that responses to questions were truthful and accurately represented the beliefs, experiences, and feelings of the respondents. Of course, it is always possible that respondents sped through the survey and did not answer the questions appropriately. Several steps were taken to ensure respondents provided accurate feedback, including a handful of attention / termination questions (i.e. "For quality control purposes, please



select choice C”) and minimum time requirements (data from surveys that were completed in less than roughly 4 minutes were not recorded). Regardless, it is still assumed respondents provided truthful and accurate data.

Finally, it is assumed that respondents understand what is implied by “classroom data use,” “student data,” and “data driven decision-making,” among other similar concepts. Again, as previously discussed, classroom data use is not limited to simple assessment of standardized test scores; it is a more inclusive concept. Therefore, when participants were taking the survey, it is assumed they answered questions related to classroom data use from that broader perspective. To be certain, the classroom data use questions were worded very specifically to avoid the narrow conceptualization. Regardless, it is still possible some respondents did not fully understand the scope of the survey questions.

### **Limitations**

Though discussed in more detail near the end of this dissertation, the study does suffer from a handful of limitations. Firstly, this study relied on a type of convenience sampling technique referred to as quota sampling. Ideally, survey-based research would rely on a nationally representative sample so the research is generalizable to the whole population of teachers in the United States. Unfortunately, the scope of this research inherently disallowed for the population of interest to be defined. That is, there is no national database repository that identifies all teachers who engaged in a data use professional development experience. Thus, the quota sample was based on the demographic (age and gender) makeup of teachers in the United States.

Finally, this study was correlational in nature, given there was no experimental manipulation. Causal claims, therefore, are absent in this dissertation. While this research does

utilize a robust and groundbreaking form of statistical testing (Hayes, 2013; 2018), nevertheless, a limitation of the study design is that all reported statistics indicate correlational relationships, not causal relationships. Hayes (2013) wrote that as long as the proper caveats associated with survey-based research are mentioned, any statistical technique, assuming it is appropriate to the research, can be utilized to test research questions and hypotheses. Several less severe limitations are discussed in the conclusion section of this dissertation.

### **Flow of Dissertation**

The next sections of this dissertation explain the hypothesized main effect in detail (the link between highly collaborative professional development experiences related to student data use and successful classroom practice), and then the mechanisms that may explain this relationship. The results of a pilot study will be briefly discussed. Next, the method by which this model was tested will be detailed. Within this discussion will be an in-depth exploration into the formal way by which these relationships can be tested statistically, as well as the instruments that were utilized. Finally, limitations of the methodology will be explored, which will then lead to a discussion of the implications of this research.

## **Chapter 2: Literature Review**

### **The Link between Collaborative Professional Development and Teacher Practice**

The effects of collaboration in a professional development experience and subsequent teacher learning / classroom practice has been well established by the literature (Cordingley, Bell, Rundell, & Evans, 2005; Darling-Hammond & McLaughlin, 1995; Erickson, Brandes, Mitchell, & Mitchell, 2005; Glazer & Hannafin, 2006; Steeg & Lambson, 2015). For example, one longitudinal study sought to illustrate a positive effect of engagement in a professional development model (named Literacy Collaborative), via increases in classroom practice of a new method by which to teach reading and literacy and student growth over time (Biancarosa, Bryk, & Dexter, 2010). This method relied heavily on peer coaching, a form of professional development collaboration. In all, nearly 300 teachers comprising 17 schools engaged in the program covering four years in duration. As each year progressed, more and more teachers were observed providing nuanced and effective literacy teaching techniques. Subsequently, student literacy skills, as measured by four metrics, increased significantly year over year (Biancarosa, Bryk, & Dexter, 2010).

However, before discussing this effect in more depth, it is important to carefully define the term “collaboration” before exploring the theoretical aspect of this phenomenon. Of course, there is no single conceptualization of the word; it is additionally conflated with other concepts, like cooperation, interrelationship, and teamwork. Thus, several definitions will be provided and then synthesized into a working definition for the sake of this research. According to Schrage (1990):

Collaboration is the process of shared creation: two or more individuals with complementary skills interacting to create a shared understanding that none had

previously possessed or could have come to on their own. Collaboration creates a shared meaning about a process, a product, or an event. In this sense, there is nothing routine about it. Something is there that wasn't there before... But the true medium of collaboration is other people. Real innovation comes from the social matrix... [and] is a relationship with a dynamic fundamentally different from ordinary communication (p. 40–41).

Buzzeo (2002) defined collaboration in the context of teachers. He wrote that collaboration was between "... two or more equal partners who set out to create a unit of study based on content standards in one or more content areas plus information literacy standards, a unit that will be team-designed, team-taught and team-evaluated," (p. 7).

The definition proposed by Montiel-Overall (2005) builds upon both. He wrote: Collaboration is a trusting, working relationship between two or more equal participants involved in shared thinking, shared planning and shared creation of integrated instruction. Through a shared vision and shared objectives, student learning opportunities are created that integrate subject content and information literacy by co-planning, co-implementing, and co-evaluating students' progress throughout the instructional process in order to improve student learning in all areas of the curriculum (p. 5).

As previously mentioned, collaboration has been interchangeably used with cooperation, community work, and teamwork, among others. For example, in the context of professional development design, Glatthorn (1987) wrote that "Cooperative professional development is a process by which small teams of teachers work together, using a variety of methods and structures, for their own professional growth," (p. 31). He further argued that this type of professional development can occur via professional dialoguing among teachers, peer supervision, peer coaching, and action research. While not as exhaustive as the definition

proposed by Montiel-Overall (2005), it is clear both definitions have significant overlap. Given the similarity of various terms used to describe a collaborative professional development experience, this dissertation will utilize a holistic approach to this general type of professional development. To do so, several scales measuring the various types of collaboration and related concepts were employed (discussed in more detail in the methods section of this dissertation).

Taken together, the following synthesized definition will be employed in service of this dissertation: Collaborative professional development is one where two or more teacher peers work together in various ways, including planning, implementing, and evaluating student work to enhance their teaching practice and subsequently increase their students' achievement. Inherent within this type of professional development is that teachers share their thoughts, ideas, and expertise with one another in an open, respectful, and judgment-free manner.

The role of collaboration in increased learning in professional learning and non-professional learning contexts has been well documented in quantitative and qualitative research. In fact, one book, albeit somewhat dated, detailed hundreds of studies related to the effects of collaboration on student learning (Totten, Sills, Digby, & Russ, 1991). The book differentiated learning effects based on subject areas, including computers, language arts, spelling, ESL, science, social studies, and special education. Perhaps more germane to this research is the book's section on vocational (adult) education, and mathematics education, given this dissertation's focus on adult teachers and data analysis (a type of math). The book detailed nine vocational education studies and 50 mathematics studies that indicated a strong link between collaboration and student learning (Totten, Sills, Digby, & Russ, 1991). For example, one study explored in this book indicated that college students in a math class who experienced a collaborative learning condition (compared to an individual / traditional learning condition)

exhibited higher levels of achievement, lower levels of anxiety, and more positive attitudes towards math (Valentino, 1988). Another study demonstrated that collaborative learning also had positive effects on business students' learning. Compared to individual efforts, business students collaboratively learning exhibited a better attitude and higher achievement scores (Michaelson & Obershain, 1983).

Collaborative learning can take various forms. A short teacher's manual provided an overview of seven models that utilized collaborative learning (Slavin, 1987). These models are: 1) Student Teams-Achievement Divisions, 2) Teams-Games-Tournament, 3) Team Assisted Individualization, 4) Cooperative Integrated Reading and Composition, 5) Jigsaw, 6) Learning Together, and 7) Group Investigation. While many of these seven models may be inherently directed towards young students, at least two lend themselves well to teacher professional learning (Learning Together and Group Investigation). Learning Together models require students to be grouped into heterogeneous teams, and then collaborate to complete carefully curated assignments that rely on scaffolded dissemination of information (Slavin, 1987). The Group Investigation model suggests learners select their own groups of two-to-six members, and, as a team, select a curated subtopic from a larger topic. Learners generate individual reports / projects that dovetail and grow upon one another based on the group subtopic. Therefore, learners must work with one another to ensure the individual projects cohesively build upon and supplement each other (Slavin, 1987).

In the context of teacher professional development, collaborative learning can also take various forms. One scholar detailed essential elements that must be included in an open-ended collaborative professional development learning model – one that is iterative and bends to the needs of the individual teacher and teacher groups (Glatthorn, 1987). First, professional dialogue

must exist among small group members during regularly scheduled meetings. “The objective is to facilitate reflection about practice, helping teachers become more thoughtful decisions makers,” (Glatthorn, 1987, p. 31). Collaborative professional development participants must also be allowed to observe their peers teaching or in the context of this dissertation, using student data to make classroom decisions. At the end of the observation stage, members provide bilateral analysis and feedback. Peer coaching is also an important element in collaborative professional development experiences; this differs from peer observation in that coaching tends to be more intensive where the coach models a desired behavior. Finally, action research projects related to the professional development program should also be employed (Glatthorn, 1987). For a data use professional development experience, an example of an action research project would be teachers actively using student data to alter their practice, measuring student achievement changes over time, and discussing / sharing their observations with their peers, who will be doing the same.

Until now, collaboration and its similar conceptual counterparts have been discussed in terms of a definition and its effects on the learning process. To understand truly the benefits of collaboration, it must be compared to something neutral, such as individualistic learning efforts. Deutsch (1973) wrote that collaboration leads to effective and efficient communication, friendliness and altruism, and a sense of pleasantness. This occurs because collaboration is itself an intrinsically rewarding and enjoyable goal structure compared to some individual behaviors (Tuomela, 2000). There are at least three possible reasons why collaborative professional development participants may be more likely than individuals who experienced isolated professional development or no professional development to successfully utilize data in their classrooms.

One mechanism that contributes to this phenomenon is the motivation to perform well. In other words, collaboration may increase people's motivation to perform at a higher level, which increases the likelihood they will actually succeed in their endeavors of learning a new skill. In a meta-analysis, it was proposed that collaborative / cooperative efforts are more likely than are individual efforts to lead to higher social support and interpersonal attraction (Stanne, Johnson, & Johnson, 1999). The authors of the meta-analysis wrote social support and interpersonal attraction may interact to lead to collaborative group members being more motivated to perform well on a task, given that strong levels of social support detected in groups may increase a member's sense of responsibility to the group (Stanne, Johnson, & Johnson, 1999). Johnson and Johnson (2009) similarly argued that motivation to perform well is higher in collaborative group settings compared to individual exercises because when collaborating, most members expect that the other members will be responsible and contribute to the group's goals. If a collaborative group member does not perform his / her role, the group will suffer, which may frustrate the other members, resulting in ostracization (Johnson & Johnson, 2009; Matsui, Kakuyama, & Onglatco, 1987). Indeed, "Failing oneself is bad, but failing others as well as oneself is worse," (Johnson & Johnson, 2009, p. 369). In all, interpersonal relationships (Johnson & Johnson, 2009; Matsui, Kakuyama, & Onglatco, 1987; Stanne, Johnson, & Johnson, 1999) may increase the motivation collaborative group members feel to perform a task at a higher degree and hence be more successful in the attainment of a goal compared to individual work.

Deutsch (1973) likewise contended that especially in smaller collaborative groups, motivation to perform well served as a precursor to more effective task performance and outcomes. Some research on motivation has indicated that when a person is inspired to perform a task, he or she is more likely than are non-motivated individuals to expend a longer quantity of



time developing the skills necessary to do well in the endeavor, which can then facilitate a better sequence of events resulting in task success (Deci & Ryan, 1985; Harackiewicz & Sansone, 1991). In sum, motivation to perform well may be a strong predictor of why collaborative groups tend to perform at higher levels compared to competitive groups or individuals – they simply spend more time working on a problem (Argyle, 1991).

Yet another possible explanation for why collaborative groups are more successful in tasks compared to individual efforts is the heightened task-based dialogue among collaborative group members. According to Argyle (1991), collaborative groups engage in task-based communication that generate diverse solutions to problems. This group dialogue allows for the creation of varied suggestions and strategies related to performing strategies and subsequent problem solving or high task performance. Because of the sheer quantity of problem solving ideas shared within collaborative groups, the correct or better solution to a problem is more likely to be attained by collaborative groups compared to individual efforts (Gabbert, Johnson, & Johnson, 1986; Johnson & Johnson, 2009; Skon, Johnson, & Johnson, 1981).

Not only do people in collaborative groups engage in task-based communication (Argyle, 1991), but these group members also tend to engage in communication that is positively and socioemotionally charged. For example, Pena and Hancock (2006) addressed communication among collaborative players of the massively multiplayer online video game *Jedi Knight 2*. Their study revealed that, compared to people playing the game solo against others, collaborative players were more likely to produce positive socioemotional messages than they were to make negative socioemotional messages. Instances of positive socioemotional comments toward the collaborative group members were congratulatory, supportive, and generally positive. Comparatively, people playing the game as individuals made disparaging and negative remarks

to the other online players. Because of this enhanced socioemotional communication, collaborative groups' morale may intrinsically increase, contributing to task success (Pena & Hancock, 2006).

It has also been stated that collaborative groups, compared to individualized efforts, are more successful in tasks because group members are able to distribute the labor among each other rather than having to perform in isolation. This especially becomes fruitful when one individual specializes or excels in a certain activity, while another person specializes in a different but complementary task within the group (Johnson & Johnson, 2009). Allowing collaborative group members to execute a skill in which they specialize increases the likelihood the overall group will succeed in its shared goals (Becker & Murphy, 1992). In collaborative professional development groups, for example, if Teacher A is especially strong in using Excel or other spreadsheet software, while Teacher B is adept at interpreting data visualizations, the grouping would be more likely to be successful in their professional development experiences than if they worked individually. Both teachers' skills complement each other, which increases the likelihood of successful learning.

While different mechanisms may explain why collaboration tends to produce successful efforts, one research team, based on their 30 years of research, proposed a theoretical model. Johnson and Johnson (2009) hypothesized their theoretical model that predicted when and how collaborative endeavors would result in increased learning. They argued that when collaborative experiences were perceived to 1) increase the likelihood the partner(s) would succeed, and 2) increase the likelihood the individual would succeed, both parties would more fruitfully engage in the endeavor, resulting in actualized success. The pathway by which this phenomenon occurred flowed from cognitive processes and affective responses. They proposed that when

social interdependence was high, team actions would be more effective, which would result in positive psychological processes (cognition), leading to promotive affective states (affective appraisals). The consequence of these serial relationships would be actual success (Johnson & Johnson, 2009).

Of course, the key to increasing the likelihood of this mediated relationship schema occurring is that positive interdependence is activated; Johnson and Johnson (1999) wrote increased positive interdependence can be externally manipulated in one of several ways. First, a professional development provider may provide joint rewards to teacher participants for increased interdependence perceptions. For example, a professional development provider could tell collaborative teams that if each member increased his or her data use in the classroom by three hours a week for three weeks, the provider would provide a free lunch. Next, interdependence increases when each team member receives a specific set of instructions or piece of information; when all team members are encouraged to work together by contributing non-overlapping pieces of expertise, the likelihood of interdependence increases. Finally, positive interdependence can be manipulated by assigning team members separate but complementary roles (Johnson & Johnson, 1999).

One qualitative study drew on similar themes as that proposed by Johnson and Johnson (1999), considering collaborative goal structures in the context of a professional development program focusing on classroom data use skills. Using a case study approach, Marsh, Bertrand, and Huguet (2015) analyzed interview and focus group data from six professional development data teams, representing four school districts and 29 participants. The groups met for a year. The analyses demonstrated that when horizontal expertise (knowledge co-created among collaborative professional development group members) and vertical expertise (knowledge

disseminated by an embedded expert) were present, learning was maximized, and teachers were more likely to utilize data in their classroom practice. The authors noted that constructive dialogue among the group members was an essential factor in the successfulness of the collaborative groups (Marsh, Bertrand, & Huguet, 2015).

In all, the literature regarding collaborative professional development structures and use of acquired knowledge in the classroom is quite clear. Collaboration in a professional development experience will most likely result in successful teacher use of the material in their respective classrooms. Thus, the first hypothesis is proposed for inquiry:

H1: Teachers who experienced professional development related to data use in the classroom that was more collaborative in nature will more successfully use data in their practice compared with teachers who experienced less or no cooperative professional development.

Of course, what is not clear is what type of collaborative efforts more fruitfully lend themselves to this hypothesis. Different researchers conceptualize collaboration differently, even using varying words (i.e. teamwork, social interdependence, cooperation, etc.) to describe a similar definition. This consideration has a direct impact on professional development providers and designers, as it informs them of what specific sorts of collaboration they ought to embed into a program. Therefore, it is important to understand which conceptualizations and subsequent operationalizations best facilitate the hypothesized phenomenon. The following research questions are posed for inquiry:

RQ1: What conceptualization or conceptualizations of collaborative professional development increase the likelihood a teacher will successfully use data in his or her classroom?

RQ2: What conceptualization or conceptualizations of collaborative professional development decrease the likelihood a teacher will successfully use data in his or her classroom?

### **The Relationship between Collaboration and Self-Efficacy**

While the hypothesized main effect between collaborative professional development and classroom practice moves the research into the realm of teacher data use, we still do not understand what mechanisms may be at play that drive this relationship. Marsh, Bertrand, and Huguet (2015) made a conclusion based on qualitative case study data that constructive dialogue may be a causal link between collaborative professional development and classroom data use. However, their data were anecdotal and not conclusive. Much is still not understood regarding what drives the hypothesized main relationship. Recall that Johnson and Johnson (2009) wrote collaboration may pique cognitive pathways, which then feed affective states, which lead to increased successful implementation of learned or practiced skills. What is inherently missing within this theory are specific types of cognitive and affective structures. Two questions remain: 1) What type of cognitive structures are impacted by collaborative goal structures, and 2) what type(s) of cognitive structure(s) lead to specific form(s) of affect? Thus, while Johnson and Johnson's (2009) theory of collaboration provides a basic structure to the mechanisms that may be at play, relying on domain-specific theories and bodies of research provide more nuance to our understanding of why collaborative goal structures lead to an increased likelihood of teachers implementing a new skill in their classroom practice.

One form of a cognitive structure that may serve as the first link in the causal mechanism chain is self-efficacy. According to the originator of the term, self-efficacy is "the belief in one's capabilities to organize and execute the courses of action required to manage prospective situations," (Bandura, 1995, p. 2). In short, self-efficacy is a person's cognitive belief that he or

she has enough internal or external resources available to complete a task, goal, or solve a problem. It should be noted that self-efficacy is a forward-thinking cognitive process. In other words, as Zimmerman (2000) wrote, “Self-efficacy judgments specifically refer to future functioning and are assessed before students perform the relevant activities. This antecedent property positions self-efficacy judgments to play a causal role in academic motivation,” (p. 84).

Self-efficacy has been associated with many positive outcomes, including academic achievement (Zimmerman, 2000), intrinsic interest in learning tasks (Zimmerman & Kitsantas, 1999), effort (Salomon, 1984), active participation, hard work, persistence, and positive affect (Bandura, 1997), among many others. Most relevant to this dissertation, though, is that self-efficacy regarding data use is an important predictor in successful use of data in the classroom (Dunn, Airola, Lo, & Garrison, 2013; U.S. Department of Education, 2009). According to Dunn, Airola, Lo, and Garrison (2013), data use self-efficacy is conceptualized across four dimensions: “1) efficacy for data identification and access, 2) efficacy for data technology use, 3) anxiety for (data driven decision-making), and 4) efficacy for data analysis, data interpretation, and the application of data to instruction,” (p. 90).

Empirical evidence has demonstrated a clear causal link between collaborative experiences and increased individual self-efficacy beliefs in the education literature. One study sought to understand under what conditions newly hired teachers experienced decreased levels of self-efficacy during their first years as educators (Chester & Beaudin, 1996). According to the researchers, there had been substantial anecdotal evidence to suggest that first-year teachers experience significantly decreased levels of self-efficacy as the year progresses. However, their longitudinal survey data of 173 teachers indicated this relationship was not universal. Their data revealed that new teachers who experienced highly collaborative development experiences saw

marked increases in their efficacy beliefs as adept teachers from time 1 to time 2 compared to their low or non-collaborative experiencing colleagues. That is, when a teacher perceived himself / herself to have experienced a collaborative relationship with his / her peers, he / she was likely to exhibit heightened levels of efficacy related to teaching skills (Chester & Beaudin, 1996).

A more contemporary quasi-experimental study came to a similar conclusion. The researchers of the study wanted to understand if collaborative learning experiences increased self-efficacy and interest in distance learning philosophy courses (Poellhuber, Chomienne, & Karsenti, 2008). The researchers were only able to recruit 54 students into a distance philosophy course, 12 of which were included in the collaboration group, and 42 of which were placed in the control group. Not surprisingly, the study lacked enough of a sample size to illustrate statistical significance; however, qualitative interviews with participants from both groups illustrated that self-efficacy beliefs related to philosophy ability were higher for those in the collaborative group compared to the control group (Poellhuber, Chomienne, & Karsenti, 2008).

There are a handful of mechanisms that may explain how collaboration leads to self-efficacy. First, Bandura's Social Learning Theory details one possible path. Social Learning Theory predicts how and when an individual will learn a new behavior, resulting in increased levels of self-efficacy. After all, self-efficacy beliefs can only emerge if an individual has some understanding or knowledge of a topic. Bandura (1995) suggested that individuals learn by watching others; that is, learning occurs via social observation and modeling. In a seminal piece, Bandura, Ross, and Ross (1961) sought to demonstrate that aggression could be a learned behavior. An even number of boys and girls ( $N = 72$ ) were either exposed to an aggressive role model condition, a non-aggressive role model condition, or a control (no model) condition. These role models were adults, who, depending on condition, punched a bobo doll and spoke

aggressively to it, or played with tinker toys, ignoring the bobo doll. After the modeler ended the treatment, the children could play in any way they deemed appropriate. Not surprisingly, those in the aggressive model condition played more aggressively, whereas those in the non-aggressive model and control conditions did not; thus, it was concluded aggression could be learned via observation (Bandura, Ross, & Ross, 1961). This study served as the empirical backbone for Social Learning Theory.

As just mentioned, a strong predictor of increased self-efficacy is viewing a modeled behavior (Bandura, 1977). However, just because an individual sees a modeled behavior does not necessarily mean he or she will learn the content and replicate the observation. A four-step causal process explains the precursors to learning and self-efficacy beliefs. First, an individual must pay attention to a modeled lesson (Bandura, 1977). If a teacher is not paying attention to a modeled exercise in using Excel for data analysis purposes, it is not likely he or she will learn to use the tool. Factors that increase attention are attraction to the modeler, interest in the modeled content, and expectations of the outcome of the modeled lesson. The next stage in the process is retention. It is essential for an individual not only to observe the modeled content, but also to encode the experience to his or her memory (Bandura, 1977). If the modeling is not memorable, then the individual will not move forward with replicating the behavior. Next, the individual observing the modeler must have the proper psychological and physical resources available to repeat the behavior or skill. Finally, the individual must be motivated to carry out the newly learned material that was being modeled (Bandura, 1977). Assuming a teacher in a data use professional development program pays attention to a modeled lesson on how to query databases, retains the memory, can reproduce the experience, and is motivated to do so, it is



likely his or her self-efficacy beliefs will likewise increase regarding the observed modeled experience.

Social observation is not the only source by which people develop self-efficacy beliefs; social persuasion and feedback, the second of the aforementioned mechanisms, also may increase or decrease a person's self-efficacy. Verbal or nonverbal social persuasion cues can boost a person's self-efficacy beliefs. But social persuasion does not work in isolation; other material supports need to be in place. Bandura (1977) wrote, "... people who are socially persuaded that they possess the capabilities to master difficult situations and are provided with provisional aids for effective action are likely to mobilize greater effort than those who receive only the performance aids," (p. 198). In the context of a professional development program, being part of a collaborative work group may increase a person's self-efficacy when the other group members verbally support him or her. However, if the professional development provider does not allow teachers to work on a computer to practice the behavior, self-efficacy will potentially falter.

Perhaps most telling of why there is a relationship between collaboration and self-efficacy, though, was demonstrated in a study conducted by the U.S. Department of Education (Means, Chen, DeBarger, & Padilla, 2011) related to classroom data use and collaboration. In this mixed-methods study, the researchers posed data use scenarios to individual teachers or small, collaborative groupings of teachers. Of the 17 scenarios, collaborative groups had a significantly higher probability of answering five scenarios more accurately compared to individual teachers completing the same scenarios. There was no statistically significant difference comparing individual to collaborative efforts for the other 12 scenarios (Means, Chen, DeBarger, & Padilla, 2011). The qualitative data suggested teachers in the collaborative group

exhibited higher levels of data self-efficacy because the group work allowed them to engage in clarification-seeking dialogue, resulting in more nuanced and competent learning. The authors suggested that as the collaborative group teachers learned more, their sense of data self-efficacy similarly increased (Means, Chen, DeBarger, & Padilla, 2011).

Taken together, observation, social persuasion, and clarification-seeking dialogue may all positively contribute to self-efficacy beliefs. Because collaborative experiences are inherently more enjoyable than individual experiences (Tuomela, 2000), the likelihood of paying attention, retaining the memory, ability for producing the behavior, and motivation for producing the behavior (in line with the social learning theory framework) is increased in a collaborative professional development experience. Moreover, because collaborative professional development experiences are also more likely to include positive forms of social persuasion and communication (Argyle, 1991), it logically follows that self-efficacy beliefs regarding the professional development material will be heightened as a result of engaging in the program. Finally, when collaborative group members engage in clarification-seeking dialogue with one another, the learning potential is increased, producing heightened levels of self-efficacy (Means, Chen, DeBarger, & Padilla, 2011).

In sum, according to Johnson and Johnson's (2009) theory, collaborative goal structures may prime positive psychological cognitions. One type of positive cognitive structure that collaboration leads to is self-efficacy. This phenomenon, which refers to a person's perceived ability to complete successfully a task or goal, occurs because of social learning and social persuasion. Because collaboration is inherently enjoyable (Tuomela, 2000), people are more likely to learn socially (Bandura, 1977). Similarly, because collaboration lends itself to positive communication, people are more likely to experience positive social persuasion (Bandura, 1977).

Clarification-seeking dialogue may also lead to increased learning, producing heightened self-efficacy beliefs (Means, Chen, DeBarger, & Padilla, 2011). All three factors can lead to increased self-efficacy evaluations. Thus, the following hypothesis is proposed for analysis:

H2: Teachers who experienced professional development related to data use in the classroom that was more collaborative in nature will experience higher levels of self-efficacy related to using data in the classroom.

### **The Relationship between Self-Efficacy and Positive Affect**

Continuing to the next causal link that may help explain the relationship between a collaborative professional development experience and the successful use of data in the classroom, in Johnson and Johnson's (2009) theory of collaboration, they suggested that cognitive responses will lead to affective states within individuals. While they are not clear about the type of affective state that will be produced by cognitive appraisals of collaborative experiences, positive affective states may be an outcome. Indeed, research has shown that positive affect can be a byproduct of self-efficacy, which, again, is a cognitive structure (Treasure, Monson, & Lox, 1996; Caprara, Steca, Paciello, & Vecchio, 2006). However, before discussing positive affect as the next mechanism, the affect and emotion literature will be discussed for some basic conceptual definitions to be explained.

Properly defining affect, also known as emotion, is difficult (Izard, 2007). However, several elements might help to explain the generation of different affective states. Affect is a psychological concept that is predicated on five elements based on a stimulus, according to Nabi (2010). First, 1) emotion and 2) physiological arousal are determined by a cognitive evaluation of an event – for example, experiencing heightened self-efficacy beliefs. Next, 3) a “subjective” state occurs based on a stimulus, which, if the stimulus is deemed as motivational, 4) it increases a person's readiness to act. Finally, 5) “motor expression” occurs as a response to the stimulus,

although it might be minor or relatively unnoticeable (Nabi, 2010). In other words, affective states are psychological feelings based on a cognition that are short-lived and vary in intensity. Furthermore, these states are created by a person's evaluation of an external event or situation (Ortoney, Clore, & Collins, 1988).

While properly defining affect may be a complex endeavor, explicating the myriad affective states has proven to be an arduous chore. Generally, scholars have gravitated towards two different camps regarding emotion / affect – the discrete perspective of emotion and the dimensional perspective of emotion. Because of different scholarly agendas and data interpretations, some researchers even contend that the discrete and dimensional perspectives are not separate from one another, and in fact, overlap significantly. Depending on the research question, the discrete or dimensional emotional perspective might both be applicable views that accurately describe human emotion (Levenson, 1988; Nyklíček, Thayer, & Van Doornen, 1997). However, much of that discussion is beyond the scope of this research. As such, this dissertation will adopt the dimensional perspective to conceptualize and operationalize positive affect. The dimensional perspective of emotion contends that affective states lie along an orthogonal, two-dimensional plane. This two-dimensional continuum is anchored by high arousal and low arousal, and pleasurable disposition and non-pleasurable disposition (Lee & Lang, 2009; Nabi, 2010). Therefore, scholars taking this perspective contend that all emotional states can fall somewhere along the two-dimensional field based on arousal and pleasure (Lee & Lang, 2009; Tellegen, Watson, & Clark, 1999).

Based on its location on the two-dimensional plane, positive affect, then, is the generalized feeling of pleasurable excitement (Isen, 1987). In other words, positive affect is a state of “high energy, full concentration, and pleasurable engagement,” (Watson, Clark, &

Tellegen, 1988, p. 1063). According to the dimensional perspective of emotion, positive affect and negative affect generally exist in separate zones of the two-dimensional scale (Green, Goldman, & Salovey, 1993; Green & Salovey, 1999). That is, positive affective states (like happiness, enjoyment, and excitement) would be found on the plane anchored by high arousal and pleasurable disposition; conversely, negative affective states would exist in the low arousal / non-pleasurable regions. These two feeling states are not negatively correlated completely, indicating there is not a perfect delineation between positive and negative affect (Green, Goldman, & Salovey, 1993). After all, the difference between nervousness (a negative affective state) and excitement (a positive affective state) oftentimes may be slight. Regardless, there seems to be a strong, negative relationship between positive affect and negative affect, supporting the argument of the dimensional perspective camp of researchers that many human emotional responses exist along an orthogonal field (Crawford & Henry, 2004; Green & Salovey, 1999; Russell & Carroll, 1999). One survey instrument that measures both forms of affect is assessed by taking the dimensional perspective (Crawford & Henry, 2004). The Positive and Negative Affect Schedule (PANAS) assumes at least 21 affective states lie along the two-dimensional field, with positive affect indicating pleasurable activation and negative affect indicating unpleasantness. This scale will be discussed in more detail in the methods section.

Empirical studies have illustrated the relationship between self-efficacy and positive affect. For example, Treasure, Monson, and Lox (1996) sought to understand the links between self-efficacy, positive affect, and the performance of high school wrestlers. A few minutes prior to a competition, the research team assessed wrestlers' (N = 70) self-efficacy and positive affect. Their data illustrated that self-efficacy positively predicted positive affect, and negatively predicted negative affect. They also indicated that when self-efficacy was more process oriented

(i.e. planning moves and strategies) rather than win-lose oriented, wrestlers were more successful. In sum, the authors demonstrated a close relationship between self-efficacy, positive affect, and performance (Treasure, Monson, & Lox, 1996). Another study came to a similar conclusion regarding self-efficacy and positive affect related to exercise (Bezoian, Rejeski, & McAuley, 1994).

One study sought to explore this relationship longitudinally, as children progressed into adults. Nearly 700 Italian students were surveyed at two points in time (Caprara, Steca, Gerbino, Paciello, & Vecchio, 2006). Self-efficacy was addressed from four perspectives: 1) perceived ability to exhibit negative affective states, 2) perceived ability to exhibit positive affective states, 3) perceived social comfort, and 4) perceived familial comfort. The researchers hypothesized that these four efficacy types would contribute to generalized positive affect at time 1, which would then predict positive affect at time 2. Not surprisingly, their analyses (which were conducted via a structural equation model) found support for their hypotheses. This study indicated that various types of self-efficacy could predict generalized positive affect (Caprara, et al., 2006).

Research has illustrated that when people experience task related self-efficacy, they tend to become pleasantly aroused; thus, they are experiencing positive affect (Bandura, 1986; 1993). Why this relationship occurs has been hypothesized in a couple different ways. First, Bandura (1997) wrote that when we are self-efficacious, we tend not to experience stress or depression related to a task; instead, we exhibit interest, desire, and pleasure. That is, our self-efficacy beliefs produce feelings of happiness. After all, if we think we have the skills necessary to complete a job, we are content and eager to begin. However, when we lack self-efficacy related to a task, we begin to fret and worry about how we will accomplish the goal (Bandura, 1997). This phenomenon is referred to as mastery expectations. When a mastery expectation is low,

people exhibit negative affective states, but when the mastery expectation is high, people tend to exhibit positive affective states.

It is possible positive affect results from mastery expectation due to the implicit relationship between mastery expectation and actualized success (Nurmi, Aunola, Salmela-Aro, & Lindroos, 2003). In other words, when we expect to succeed, we tend to succeed more often than fail. Indeed, there is a body of literature that demonstrates a strong link between success and positive affect (Ntoumanis & Biddle, 1999). For example, one study empirically demonstrated that when people succeed, they exhibit heightened levels of positive affect. Egloff, Schmukle, Burns, Kohlmann, and Hock (2003) collected self-report affect scores via the PANAS from individuals. Participants were then tasked with creating words from anagrams; the anagrams' difficulty levels were varied, ensuring either failure or success. After the task, affect was measured again via the PANAS. Those in the success-ensured group exhibited increased positive affect from time one to time two, whereas those in the failure-ensured group exhibited decreased positive affect from the two points of time (Egloff et al., 2003). Thus, if we expect to succeed, we may experience positive affect.

Another line of research provides perhaps a more nuanced explanation of why mastery expectation links self-efficacy and positive affect. The appraisal theory of emotion states that people's affective states can be determined by their appraisal of a situation. In other words, "it is the interpretation of events, rather than events themselves, that cause emotions," (Roseman & Smith, 2001, p. 6). Some outcomes of events are so impactful to humans that most people, regardless of individual differences, tend to appraise those results similarly, yielding the same or comparable affective states (Roseman & Smith, 2001; Smith & Lazarus, 1990).

What further drives a person's evaluation of a situation is motive consistency. Roseman,

Antoniou, and Jose (1996) empirically demonstrated that motive consistency is a primary mechanism that dictates how a person will appraise a situation and the subsequent affective state that will result. If a person evaluates a situation as consistent with his or her goals, a positive affective state is more likely to result than a negative affective state. For example, Teacher A does not use student data to make decisions. However, Teacher A sees many of her peers talking about student data one afternoon and learns that using data can help her teaching. She reads up on the topic more and determines using student data can be a powerful aid in her classroom. Thus, she enrolls in a professional development program that will train her on how to use student data. Making data driven decisions has now become consistent with her motives. Several other studies have supported the conclusion that when events are appraised as motive-consistent, positive affect is a likely outcome (Roseman, Dhawan, Rettek, Naidu, Thapa, 1995; Roseman, Antoniou, & Jose, 1996; Scherer, 1993; Wallbott & Scherer, 1988).

It is also important to note that some studies have illustrated the opposite regarding positive affect and self-efficacy – that is, positive affect may lead to greater self-efficacy (Baron, 1990; Leganger, Kraft, & Roysamb, 2000). Therefore, the relationship between positive affect and success might be bidirectional, indicating a strong connection between these two concepts.

Taken together, research has demonstrated a close link between increased levels of self-efficacy and heightened positive affect. According to Bandura (1977), when people feel confident in their ability to complete a task (that is, they are self-efficacious), they tend to experience positive affect. After all, knowing one has the capabilities and resources to complete a task would not instill feelings of dread, but rather, feelings of comfort and calmness. An individual's sense of mastery expectation may govern this link. It is possible that because mastery expectation is linked so closely with success, and success produces positive affect



(Ntoumanis & Biddle, 1999), mastery expectation may also produce positive affect. Another explanation for why this relationship occurs may be due a person's interpretation of completing a task (Nurmi, Aunola, Salmela-Aro, & Lindroos, 2003), which results in a positive affective state (Roseman & Smith, 2001). Thus, the following hypothesis is proposed for analysis:

H3: Teachers who experience higher levels of self-efficacy related to using data in the classroom will be more likely than will their lower self-efficacy counterparts to experience increased levels of positive affect in relation to using data.

### **The Relationship between Positive Affect and Successful Classroom Data Use**

The final strand of the mediated model proposed by this dissertation – the link between positive affect and successful classroom data use – can be well explained by a theoretical body of work related to positive psychological states and success from a multitude of angles (teacher success, student success, teacher task success, etc.). It is not surprising that having a positive disposition results in a successful outcome; when someone feels better or has a sunnier outlook, that individual does not have as many hurdles in his or her way to success. For example, one study sought to explore longitudinally the relationship between positive affect and task success with teachers (Duckworth, Quinn, & Seligman, 2009). The study (N = 390) assessed teacher grit, positive explanatory ability, and life satisfaction at the beginning of the year at under-resourced public schools. At the end of the year, teacher effectiveness was measured via student achievement gains; not surprisingly, all three predictors were associated with student learning gains (Duckworth, Quinn, & Seligman, 2009).

Another study addressed the effects of teacher positive affect on student interest (Keller, Goetz, Becker, Morger, & Hensley, 2014). It was hypothesized that teacher enthusiasm, a form of positive affect, would lead to increased student perceptions of teacher enthusiasm, which would result in increased student interest on a topic. To test their hypotheses, the researchers

surveyed teachers ( $N = 75$ ) and their students ( $N = 1,523$ ) in Switzerland. Their data, as tested via a structural equation model, demonstrated support for their hypotheses – student interest piqued when teachers exhibited enthusiasm during their instruction (Keller, Goetz, Becker, Morger, & Hensley, 2014).

Perhaps most telling about the link between positive affect and broad successfulness, though, was a seminal meta-analytic study that considered cross-sectional, longitudinal, and experimental studies that analyzed a form of the positive affect / success hypothesis (Lyubomirsky, King, & Diener, 2005). In all, the research team considered over 200 published papers and a handful of methodologically rigorous dissertations. Of these studies, there were nearly 300 samples representing over 275,000 participants and about 300 unique effect sizes. Needless to say, this meta-analysis was exhaustive (Lyubomirsky, King, & Diener, 2005). While the researchers looked at various outcomes of positive affect, including health and wellness, work life, social wellness, perceptions, and sociability, among others, one theme was especially pertinent to this dissertation: the effect of positive affect on creativity / problem solving. This was further broken into 1) flexibility / originality on tasks and 2) complex mental task performance, when applicable. For the cross-sectional class of data, the average performance in these categories was moderate ( $r = 0.26$ ). Few longitudinal studies explored the link between positive affect and success; however, the handful that did illustrated a positive effect. Most telling, though, was the experimental data effect sizes; both creative problem solving and original thinking effect sizes in experiments were moderate ( $r = .25$ ). Taken together, the meta-analysis clearly details a strong relationship between positive affect and successful completion of a creative problem-solving task (Lyubomirsky, King, & Diener, 2005).

Creative problem solving has been defined as a process linking original thought and novel solutions. Indeed, one scholar wrote creative thinking is a person's linkage and combination of seemingly unrelated elements to come up with a solution or process to a problem (Mednick, 1962). Newell, Shaw, and Simon (1958) elucidated four stages in the creative problem-solving process. 1) The product or outcome of the process is original and has value. 2) The thought process is novel; it may (and frequently does) require outright rejection of previously defined processes and procedures that are currently considered the norm. 3) The thinker must be persistent and motivated to the process and solution. 4) Much of the work the thinker needs to complete is providing form and structure to a problem that is not well articulated or defined. The thinker spends a considerable amount of time constraining and exploring the problem (Newell, Shaw, & Simon, 1958).

In the context of the classroom, successful use of data is itself a creative problem-solving exercise. In other words, when teachers use data in the classroom, they are simply exerting creative thinking skills to solve an ill-defined problem. A priori, teachers do not necessarily know what the data will tell them about student performance until after the data have been mined, visualized, manipulated, and then interpreted. This process is not well defined, and it is iterative. A teacher adept at using student data to make decisions does not necessarily follow a systematic analysis guide when interpreting output. He or she must be flexible, discover the data's stories, and create an intervention plan that benefits each student individually. Therefore, the whole act of classroom-wide data analysis is in and of itself a creative thinking endeavor.

Why the relationship between positive affect and successful completion of a problem-solving task may exist has also been posited in various strands of research. One explanation for

this phenomenon has relied on heuristic shortcuts as an explanatory mechanism. According to Lyubomirsky, King, and Diener (2005):

In recent years, a perspective has emerged that people in positive moods interpret their affect as signifying that events are going well. Thus, they are quicker to make decisions and are likely to use general heuristic answers learned in the past. After all, if all is well, then past successful answers are likely to work, (p. 839).

When an individual is experiencing a positive affective state, he or she is subsequently more likely to recall existing knowledge bases wherein that person has previously succeeded, because the experience or setting is evaluated as safe and in concert with one's goals (Lyubomirsky, King, & Diener, 2005). In other words, we rely on a similar cognitive structure we developed at point 1 when we experience positive affect in a related situation at point 2.

When people are experiencing positive affective states in relation to a new task that is thematically similar to a previous task, the emotional disposition leads to a quicker, more efficient recalling of what did and did not work in the previous task. By employing "what worked" in a previous task, happier individuals are more likely than their neutral affect or negative affect counterparts of being successful (Lyubomirsky, King, & Diener, 2005). Research conducted by Isen and Means (1983) empirically supported this claim; individuals who were induced to experience a positive affective state were more likely than were others to complete successfully a complex goal (one that also required creative problem solving). These individuals sorted through unimportant and spurious information; they instead relied on relevant heuristic shortcuts to arrive at sound, quick conclusions (Isen & Means, 1983). In short, "Those in a good mood will excel when the task is complex and past learning can be used in a heuristic way to

more efficiently solve the task or when creativity and flexibility are required,” (Lyubomirsky, King, & Diener, 2005, p. 840).

Another causal explanation for this phenomenon is related to a link among positive affect, safety, and security. When an individual is experiencing a positive affective state, he or she, more often than not, feels comfortable in the surroundings and environment. There are few security concerns, resulting in a feeling of playfulness (Fredrickson, 1998; 2001). When we are playful, we are more likely than are non-playful individuals to experiment with divergent solutions to a task. As previously mentioned, creative problem solving requires individuals to draw upon seemingly unrelated concepts to reveal novel solutions (Mednick, 1962; Newell, Shaw, & Simon, 1958). Therefore, playfulness encourages the linking of unrelated thoughts and ideas, increasing the likelihood of a successful execution of a mental task.

Taken together, there is a large body of literature that has indicated a significant link between positive affect (Lyubomirsky, King, & Diener, 2005) and the successful execution of a task, especially when that task requires creative problem solving (Fredrickson, 1998; 2001; Isen & Means, 1983). This relationship has been exhibited in the classroom setting (Keller, Goetz, Becker, Morger, & Hensley, 2014). It has been proposed that positive affect leads to successful task completion because experiencing positive affect may result in the priming of efficient heuristic shortcuts (Isen & Means, 1983). It has also been suggested that because those experiencing positive affective states are likewise more playful, they are more likely to toy around with seemingly unrelated ideas, producing novel and successful completion of tasks (Fredrickson, 1998; 2001). Therefore, the next hypothesis is proposed for inquiry:

H4: There will be a positive relationship between data positive affect and successful teacher data use in his / her practice. That is, teachers with higher data positive affect will likewise more successfully use data in their teaching practice.

### **Additional Research Considerations**

Given the extant literature on cooperative professional development, self-efficacy, positive affect, and successful task completion, the final hypothesis, regarding a mediated relationship, is proposed for analysis:

H5: A mediated path will exist between high cooperative professional development experience related to data use and successful use of data in a teacher's practice. This path will be positively mediated, in sequence, by data self-efficacy and positive affect.

While this proposed mediated pathway may prove to be significant in aggregate, an individual group differences may interact with the proposed relationship. That is, it is possible teacher tenure may moderate the proposed relationship. For example, one study indicated that as teachers aged, they were less likely to engage with in-service training experiences; these teachers were also more likely to avoid collaboration with other teachers (Richter, Kunter, Klusmann, Lüdtke, & Baumert, 2001). Data were collected from 1,939 secondary school teachers in Germany and analyzed statistically. However, the study did indicate that longer-tenured teachers were more likely than were their younger counterparts to utilize and learn from professional literature, indicating that more tenured teachers still experience some form of professional development. A qualitative study illustrated that older teachers, compared to younger teachers, were less motivated to engage voluntarily in professional development programs (Janssen, Kreijns, Bastiaens, Stijnen, & Vermeulen, 2013). This study was based on 41 semi-structured interviews with teachers in schools where professional development was mandated. In all, the

literature on a relationship between the effectiveness of professional development and teacher age is sparse. Moreover, both the aforementioned studies were based on non-United States samples; thus, it is possible these relationships would not manifest themselves among American educators. Taken together, just because older teachers do not engage in professional development as frequently as do their younger counterparts does not mean, though, that a collaborative professional development experience will not benefit them similarly. It is possible age may interact with the hypothesized mediated pathway at some capacity, but given the paucity of the localized empirical data on the topic, a final research question was asked:

RQ3: Does teacher age interact with the hypothesized pathway linking collaborative professional development and successful use of student data?

## **Chapter 3: Methodology**

### **Dissertation Methodology**

This section of the dissertation will address the method, instruments, and statistical testing techniques that will be used to test the hypotheses and research questions. Again, a pilot study was conducted to identify if certain instruments effectively and properly conceptualized and operationalized the various terms studied as part of the larger research project. While all the hypotheses were supported by the pilot data, areas for instrument improvement were identified. The pilot test will first be detailed, followed by the methodology utilized for this dissertation.

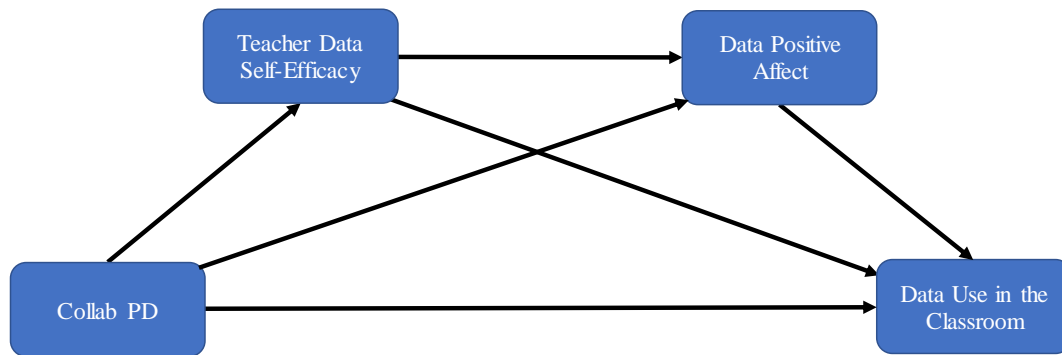
### **Pilot Test**

Because hypotheses and instrument selections are an important element in the research process, a pilot test was conducted in the summer of 2017. The following general hypothesis was tested by the pilot study:

H: (H1) A mediated path will exist between high collaborative professional development experience related to data use and increased use of data in a teacher's practice. This path will be positively mediated, in sequence, by data self-efficacy (H2) and positive affect (H3), which then concludes with teacher data use (H4). The following model represented the hypothesis in this pilot study (Figure 1).



Figure 1

*Hypothesized Mediated Path*

In all, 54 educators completed a survey to address the hypothesis during the summer of 2017; participants were recruited via Facebook and not provided compensation for completion of the survey. The average age of the respondents was 39.57 (ages ranged from 23 to 64,  $SD = 10.94$ ), and the average years of teaching was 13.67 (years teaching ranged from 1 to 43,  $SD = 10.26$ ); the majority of the respondents was female (77.8%) and white (90.7%). The entire sample was comprised almost exclusively of teachers (98.1%), with only one administrator represented. Additionally, 87% of the respondents were full time teachers, while 9.3% were part time teachers, and 3.7% were not currently working as teachers but had been so in the recent past. Most of the respondents taught at public schools (87%), and all grades, from pre-K to college, were represented in the sample, though there was a slight skew in favor of high school and college teachers. Finally, due to a survey programming glitch, teacher subject specialty (i.e. math, science, special education, etc.) was not reliably captured by the survey.

**Predictor and outcome variables.**

To operationalize the first predictor variable (collaborative professional development experience related to data use), 10 questions addressed the collaborative nature of the professional development experience the respondent believed to have been the most meaningful.

These items were adapted from an instrument developed by Barnard, Paton, and Rose (2007).

The items were highly reliable (Cronbach's  $\alpha = .94$ ) and were added together. This variable was then dichotomized by taking a median split ( $16 - 37 = \text{low collaboration}$  and  $37 - 45 = \text{high collaboration}$ ).

The second predictor variable addressed the teachers' sense of self-efficacy related to their use of data, which was adapted from an instrument developed by the father of self-efficacy, Albert Bandura (2006). Respondents were asked to indicate their level of agreement (5-point scale) with statements preceding the following text: "In relation to my use of data in the classroom, I know I can...." The reliability was strong (Cronbach's  $\alpha = .91$ ); thus, the 16 items were added together.

The final predictor value, positive affect, was operationalized using items from the Positive and Negative Affect Schedule (Watson & Clark, 1999; Watson, Clark, & Tellegen, 1988). Respondents were invited to indicate the degree (5-point scale) to which they experience various feelings when they think about using data in the classroom. Again, the reliability of the items was strong (Cronbach's  $\alpha = .96$ ), and they were subsequently added together.

The outcome variable was operationalized using two items:

- 1) How frequently do you use data in the classroom as part of your teaching practice?
- 2) What percentage of your planning time is designated to analyzing student data to inform your teaching?

Despite being measured via two different scales (question 1 is categorical while question 2 is ratio), both variables can be conceptualized as interval scales, with higher values indicating more frequent use of data. Thus, both items were transformed to Z scores, which were then averaged together ( $r = .34$ ,  $p < .05$ ).

Finally, research has demonstrated that the longer an individual engages in a high quality professional learning experience, the likelihood is increased that he or she will utilize the learned material in the classroom (Kedzior & Fifield, 2004). As such, it was determined that could be a confounding variable in the overall model. To address this concern, a survey question was asked regarding the length of time the teacher spent in the professional development experience. The mean of this variable was 10.11 hours.

### **Results.**

A serial mediation model (specifically, Model 6) was employed utilizing Hayes' SPSS macro PROCESS (Hayes, 2013). To calculate the confidence intervals of the various effects, 5,000 bootstrapped samples were simulated. This process will be discussed in much more detail in a later portion of this dissertation.

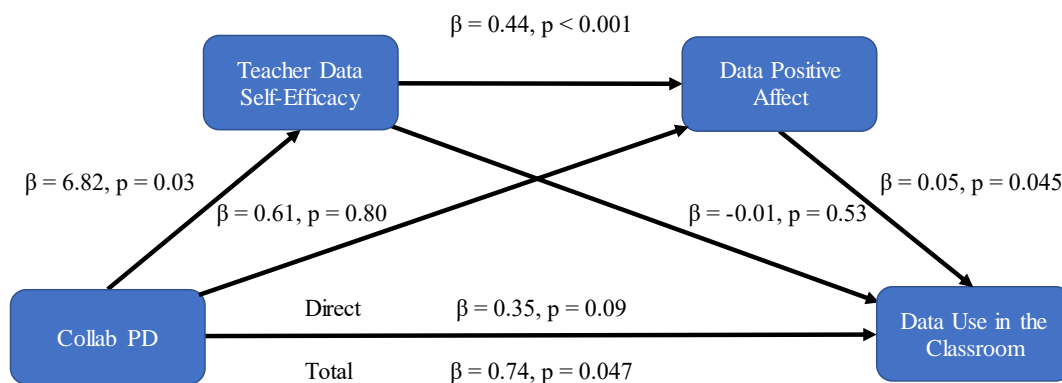
There is considerable evidence to suggest the serial mediation model with teacher data efficacy and data positive affect, in sequence, explains the relationship between collaborative professional development data use experience and data use in the classroom. In step one, there is a positive relationship between collaborative professional development data use experience and teacher data efficacy;  $b = 6.82$ ,  $t(51) = 2.21$ ,  $p = .03$ ;  $F(2, 51) = 2.43$ ,  $p = .10$ ,  $R^2 = 8.71\%$ . hours spent, the control variable, was not significant in this step ( $b = -0.03$ ,  $t(51) = -0.42$ ,  $p = .67$ ). In step two, we see a strong relationship between teacher data efficacy and data positive effect,  $b = 0.44$ ,  $t(50) = 4.38$ ,  $p < .001$ ; the relationship between collaborative professional development data experience and data positive affect was not significant,  $b = 0.61$ ,  $t(50) = 0.26$ ,  $p = .80$ ,  $F(3, 50) = 8.37$ ,  $p < .001$ ,  $R^2 = 33.44\%$ . The control variable was again not significant in this step ( $b = 0.09$ ,  $t(50) = 1.667$ ,  $p = .10$ ). In the third step, there is no relationship between teacher data efficacy and data use,  $b = -0.01$ ,  $t(49) = -0.64$ ,  $p = .53$ . However, there is a positive association

between data positive affect and data use ( $b = 0.05$ ,  $t(49) = 2.06$ ,  $p = .045$ ), while collaborative professional development data experience was not significant ( $b = 0.65$ ,  $t(49) = 1.75$ ,  $p = .09$ ). The control variable factored significantly into this model ( $b = 0.04$ ,  $t(49) = 4.3$ ,  $p < .001$ ). The overall model was significant –  $F(4, 49) = 9.73$ ,  $p < .001$ ,  $R^2 = 44.26\%$ . In the final step, there is a positive main effect between collaborative professional development data experience and data use ( $b = 0.74$ ,  $t(51) = 2.02$ ,  $p = .047$ ;  $F(2, 51) = 16.39$ ,  $p < .001$ ,  $R^2 = 39.13\%$ ). Likewise, the control variable was again significant in this model ( $b = 0.04$ ,  $t(51) = 4.77$ ,  $p < .001$ ).

Given the p-value of the direct effect in the serial mediation model is insignificant while the main effect is significant (that is, X directly predicts Y with no mediation), the two variables completely mediate the relationship between X and Y in sequence. The completely standardized indirect effect of X on Y was significant, as the confidence intervals did not cross over zero (Effect = 0.05, Bootstrap LLCI = 0.01, Bootstrap ULCI = 0.18). In short, all hypotheses were supported (see Figure 2).

Figure 2

*Mediated Path Results of the Pilot Study*



**Conclusions and next steps.**

Despite representing a relatively small sample size, this pilot study demonstrated that a mediated path may exist between collaborative professional development experiences related to data use and applied use of data to inform instruction. In sequence, a significant mediation path passes from collaborative professional development, to teacher data efficacy, to data positive affect, and then to use of data in the classroom.

While this pilot study did support the hypothesized mediated relationship between collaborative data professional development and classroom data use, there are several methodological elements that were rectified by the dissertation research. First, the pilot study did not include data from teachers who did not engage in a professional development program related to data use; doing so in the dissertation research provided more nuance to our understanding of the relationship. Next, there were perhaps more appropriate instruments than was used in the pilot study that will better operationalize the relationship. For the finalized instruments that were employed in the dissertation, please see the instruments section of the method (next) and Appendix 1. Similarly, collaborative professional development was only operationalized in one way. Recall one of the goals of the dissertation research project is better to understand what type of professional development collaboration best facilitates the hypothesized relationship. The research will operationalize collaboration from a multitude of perspectives. Additionally, given the small sample size, only one control variable was utilized in the pilot study; the dissertation project employed several more control variables (again, these will be discussed in the next section). As previously mentioned, a programming glitch did not allow for a successful capture of data related to teachers' specialty (i.e. math, history, social studies, special education, etc.). Because special education teachers tend to be adept users of data due to

legal mandates (Wilson, Michaels, & Margolis 2005), that field will be properly captured.

Therefore, this data will be properly collected by the dissertation project. In all, the pilot study demonstrated that there was at least a relationship among the four variables of interest (collaborative professional development, data self-efficacy, data positive affect, and data use).

However, the proposed dissertation research project provided more nuance and methodological rigor compared to what was present in the pilot analysis.

### **Full Study Methodology**

To test the research questions and hypotheses for this dissertation, a convenience sample of teachers from across the United States were convened and surveyed. Given the pilot test was able to support the hypotheses with just 54 respondents, increasing the quantity of teachers ensured more statistical power and variance were present. To be certain of the number of respondents that were needed, a power analysis, using the G\*Power analytic software, was conducted making the following assumptions:

- 1) The effect size will be small-to-medium
- 2) P values at or less than 0.05 will be considered as the cutoff for determining statistical significance
- 3) A power value of .95 is needed
- 4) A total of 9 predictor variables can be utilized (3 primary predictors and 6 control predictors).

According to the power analysis results, a total of 166 respondents was needed. To be conservative, the goal of this research was to collect data from at least 200 educators.

Ideally, the data would be collected from a nationally representative sample of teachers, allowing for this research to be generalized to the overall population. Unfortunately, a lack of

sufficient funding did not allow for a generalizable sample to be convened. An alternative method, quota sampling, was employed. Quota sampling is a purposive type of convenience sampling, improving upon some of convenience sampling's weaknesses. This quota sample method, while not perfect, is better than simple convenience sampling, in that the data more closely resemble a population's characteristics, even if the data were collected conveniently. According to Cumming (1990), a quota sample, which is frequently used in market research studies, "... involves selection of subjects into various sub-groups of the study sample. These sub-groups are defined by criteria, known as quota controls, such as age and sex ... Quota sampling ensures representativeness in terms of the quota controls..." (p. 132).

There is evidence to suggest that despite being collected via a quota sample, data convened by using this method does not differ significantly from data collected via probability sampling. In his study of quota sampling, Cumming (1990) compared the characteristics of people in two waves of a health survey. One wave of the study reflected the quota sampling method ( $N = 1,727$ ), while the other wave reflected a probability sample ( $N = 484$ ). Of the 15 health questions asked of the survey, only 3 items were statistically and significantly different from one another ( $p < .05$ ). Of course, this is not to mean that quota samples are suitable proxies for representative samples. It just means that limitations associated with non-random probability sampling ought to be considered when discussing the analyses of quantitative data (Acharya, Prakash, Saxena, & Nigam, 2013). All told, quota sampling is not a perfect panacea to the problems associated with convenience sampling; however, it is a marked improvement.

Data were collected over a 20-day period in February 2018. The researcher used Qualtrics to design the survey and manipulate its flow, ensuring questions within sections were randomized, as well as some of the sections themselves (discussed in more detail later).

Recruitment for participation occurred in four ways. First, the researcher reached out to his social network groups, appealing to K-12 educators from across the United States to complete the survey. Over the course of one week, 34 educators successfully completed the survey by utilizing this recruitment method. Next, students in select graduate classes at the University of Kansas were invited to complete the survey for credit in their respective courses via the Sona Systems research pool. A total of 7 educators completed the survey; however, data were valid for only 6 participants. The researcher also offered teachers on Reddit K-12 teacher groups a \$2 Amazon gift card to complete the survey, assuming qualifying criteria were met (i.e. the teacher properly answered questions intended to ensure the participant was paying attention, the person was actually a K-12 teacher, etc.). This recruitment method garnered 36 successful completions. However, data from 5 teachers were subsequently deleted, as the participants did not reside in the United States.

Finally, the researcher was awarded a \$1,000 research stipend from the University of Kansas to collect data. The researcher used these funds to collect data from 197 educators across the United States recruited by the Qualtrics Survey Panel service. Educators who completed the survey in this manner were also subjected to exclusion criteria, as well as quotas based on 1) Age, 2) Gender, and 3) Response to a screener question (discussed in more detail later). The four datasets were combined, resulting in a final sample size of 268. Across all four methods of data collection, enough data existed by which to create a quota sample of 207 teachers.

To compile the quota sample, the necessary count of participants was randomly selected from the available quantity of participants in each age and gender bracket. For example, data from 63 teachers who were female and 50-years-old or greater were collected; however, the quota counts necessitated data from only 50 teachers who met that criteria. Thus, data from 50 of



the available 63 participants were randomly selected for inclusion in the quota sample. The quota counts were compiled from a National Center for Education Information study, which detailed teacher demographics in the United States by age and gender (Feistritzer, Griffin, & Linnajaryi, 2011). The actual quota distributions by age and gender will be discussed in the descriptive statistics section of this dissertation. Table 1 displays the demographic breakouts from which the quota sample of this research were based, as well as the quota sample representations. Note that all percentages were rounded up to the nearest percent; as such, the sum of the percentages was over 100%, resulting in a total sample size for the quota sample being 207 educators needed.

Table 1

*National Teacher Demographics and Quota Sample Demographics*

Age	Male (Represented by Quota Sample)	Female (Represented by Quota Sample)
< 29	4% (N = 8, 3.9%)	19% (N = 38, 18.4%)
30-39	5% (N = 10, 4.8%)	24% (N = 48, 23.2%)
40-49	4% (N = 8, 3.9%)	18% (N = 36, 17.4%)
50+	5% (N = 9, 4.3%)	25% (N = 50, 24.2%)

**Survey rationale.**

As per the committee's feedback in December 2017, several changes, additions, and amendments were requested to be made to the survey. This brief section will outline those modifications.

First, in the data self-efficacy and data positive / negative affect items, it was recommended the word "feel" was replaced with "think" or "believe." Those changes were made where applicable.

Continuing, in the original survey, all the questions were positively themed. It was recommended that a handful of questions be negatively-themed to ensure survey takers were paying close attention in the Likert-type questions. Those changes were made throughout the various questions as appropriate.

The survey utilized various scales to address the concepts being studied, including semantic differential scales (as was recommended), 5-point Likert-type scales, 7-point Likert-type scales, open-ended numerical responses, and even open-ended text in order to collect qualitative feedback. In all, the survey utilized different scales in order to diversify the types of data collected.

It was recommended that, as part of the questions that addressed the outcome variable, that survey participants were provided with data use scenarios. In other words, teachers would be asked "what would you do" or "how would you solve this problem?" One study did a nice job of asking teachers to complete student data use scenarios (Means, Chen, DeBarger, & Padilla, 2011). Recall that those responses, which were scored for accuracy, served as the outcome variable of the aforementioned study. Unfortunately, these questions were very time-consuming to complete in the study. Given the funding deficiencies of the current study, and the desire to keep the survey completion time average under 20 minutes, it was impractical to ask the survey participants such questions. Instead, the outcome variable was operationalized in three ways: 1) Frequency, Duration, and Intensity, 2) Applied Competency of Classroom Data Use, and 3) Perceived Effectiveness of Classroom Data Use. These three types of operationalizations should sufficiently encapsulate the outcome variable, while still considering survey completion time, to collect accurate data.

Much work has been done in generating various measures of self-efficacy. It was suggested this dissertation utilize the self-efficacy questions designed by Enochs and Riggs (1990). While that scale has been employed successfully in other studies (see Brouwers & Tomic, 2000, Ross & Bruce, 2007, and Tschannen-Moran & Hoy, 2001, among others), it was ultimately decided to use the instrument designed by Dunn, Airola, Lo, and Garrison (2013). These questions directly address data use self-efficacy, and have been well validated (Dunn, Airola, Lo, & Garrison, 2013), whereas the Enochs and Riggs (1990) items are related to science teacher self-efficacy. Thus, by using the Dunn, Airola, Lo, and Garrison (2013) instrument, no question modification was needed, avoiding any possible validity issues.

#### **Instruments and variables.**

As previously mentioned, in most cases, more than one question or item on the survey addressed a similar concept in order to operationalize the various predictor, mediator, moderator, and outcome variables. First, the descriptive statistics regarding the control variables will be described, followed by the predictor variables, and then finally, the outcome variables. See Appendix 1 for the survey.

#### ***Outcome variables.***

The first outcome variable (referred to as Frequency, Duration, and Intensity) was assessed by three items. One question addressed frequency of student data use (1 = Haven't Used, 9 = At least Once a Day), another question addressed duration of time spent utilizing student data (open-ended numerical response, ranging from 0 to 100), while a final question, measured on a semantic differential scale, addressed the intensity of attention the teacher affords to classroom data use (0 = Not Intently, 10 = Intently). Because all three items were measured

using separate scales, all responses were transformed into standardized scores (Z-scores) and then averaged together (Cronbach's Alpha = .76,  $\mu = 0.00$ , SD = 1.00).

However, frequency, duration, and intensity questions presuppose that just because an individual utilizes data frequently, that teacher is doing so successfully. While that assumption is on the surface valid, successful data use ought to be explicitly addressed. Fortunately, some items from the data use efficacy scale (Dunn, Airola, Lo, & Garrison, 2013) could be modified to directly measure successful teacher data use. The second outcome variable (Applied Competency of Classroom Data Use) was addressed by 12 items (several of which were recoded) and averaged together (Cronbach's Alpha = 0.92,  $\mu = 3.72$ , SD = 0.78). The scale was anchored by strongly disagree (1) to strongly agree (7).

Finally, Perceived Effectiveness of Classroom Data Use served as the third outcome variable. Three items addressed this variable, each consisting of a unique, 11-point semantic differential scale (Strong / Weak, Lacking / Excellent, and Supported / Unsupported). Generally, the questions asked educators about their effectiveness of using student data, the quality of the district data retrieval system, and the support teachers receive from school leaders regarding student data use. The variable was sufficiently reliable (Cronbach's Alpha = 0.83,  $\mu = 6.41$ , SD = 2.14).

All three outcome variables were positively and significantly correlated with one another, but not perfectly, which indicates that each outcome variable does assess classroom data use from unique perspectives (see Table 2 for the correlation matrix).

Table 2

*Correlation Matrix of the Three Outcome Variable*

	Frequency, Duration, and Intensity	Applied Competency of Classroom Data Use	Perceived Effectiveness of Classroom Data Use
Frequency, Duration, and Intensity	$r = 1$	$r = 0.61, p < .001$	$r = 0.58, p < .001$
Applied Competency of Classroom Data Use		$r = 1$	$r = 0.66, p < .001$
Perceived Effectiveness of Classroom Data Use			$r = 1$

***Control variables.***

As previously noted, there were five control variables (duration, content focused, active learning, coherence, and collective participation) identified for inclusion within the study, representing effective PD traits (Garet, Porter, Desimone, Birman, & Yoon, 2001), and trait collaboration. Participants who did not experience any professional development experience related to data use were appropriately coded based on each scale. First, duration of professional development experience was operationalized by multiplying a question addressing the percentage of professional development time related to classroom data use with another question related to the quantity of hours the participant spent in a data use professional development experience (PD Experience  $\mu = 11.86$ ,  $SD = 25.45$ ; Whole Sample  $\mu = 8.65$ ,  $SD = 22.35$ ). This product served as the duration control variable. Content focused (1 = No Emphasis, 4 = Major Emphasis) was addressed by one item (PD Experience  $\mu = 2.74$ ,  $SD = 0.78$ ; Whole Sample  $\mu = 2.00$ ,  $SD = 1.39$ ). Active learning was addressed by six items (1 = Very Much Describes my Experience, 7 = Does Not Describe My Experience at All); the items were averaged together

(Cronbach's Alpha = .78, PD Experience  $\mu = 3.95$ , SD = 1.45; Whole Sample  $\mu = 5.04$ , SD = 2.19). Coherence was addressed by three items (1 = Strongly Disagree, 5 = Strongly Agree), which were averaged together (Cronbach's Alpha = .86, PD Experience  $\mu = 3.65$ , SD = 0.95; Whole Sample  $\mu = 2.66$ , SD = 1.82). Three items addressed collective participation (1 = Strongly Disagree, 5 = Strongly Agree), which were averaged together (Cronbach's Alpha = .72, PD Experience  $\mu = 3.62$ , SD = 0.99; Whole Sample  $\mu = 2.67$ , SD = 1.82). All items were based on questions generated in the pivotal PD study executed by Garet, Porter, Desimone, Birman, and Yoon (2001).

Another confounding variable that should be considered is teachers' predisposition to collaboration. That is, if a teacher already exhibits strong trait collaboration skills, that may influence the benefit of engaging in a collaborative professional development experience. Trait collaboration was addressed by four items, which were subsequently averaged together (Cronbach's Alpha = .79, PD Experience  $\mu = 3.96$ , SD = 0.88; Whole Sample  $\mu = 2.89$ , SD = 1.92).

### ***Predictor variables.***

First, a screener question was displayed to participants. The intent of this study was to determine how a professional development experience relates to successful use of data in the classroom. It was possible many teachers have never completed a professional development experience related to data use. While it is still prudent to capture data from people who did not complete a data use professional development experience, there ought to be a cap; the pilot study indicated an almost a 3-to-1 ratio of teachers who did not complete a data use professional development experience to teachers who did complete such an experience. Therefore, the following question was first displayed to teachers.

In the past 3 years, have you ever engaged in a teacher professional learning experience where the concept of data use in the classroom was discussed?

To ensure that those who answered “No” were not overrepresented in the data, only the first 75 who answered the question negatively would be allowed to continue. Once the quota was met, those individuals were disallowed to complete the survey. In the quota sample, 56 teachers who answered “No” were represented.

Collaborative learning was originally conceived of as three separate constructs. First, the Teamwork Scale is a brief, four-item instrument, of which two items were reverse coded. These two items were recoded in accordance with the other two items, so reliability statistics could be computed (Waldman, 1997). The instrument addresses feelings of teamwork and can be modified as needed. Each question was assessed via a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The Cronbach’s Alpha value of the four items was .78. The items were averaged together, and the mean was 3.79 (SD = 0.81). The individuals who did not see the items, because it did not apply to them, were coded as 0; the mean of the complete quota sample was 2.76 (SD = 1.82).

Shared knowledge building (Chan & Chan, 2011), the second operationalization, was addressed by six items, with a Cronbach’s alpha statistic of .80. The instrument assesses the perceived quality of knowledge generated from a collaborative experience. While this instrument is 12 items, only 6 were asked in consideration of the survey experience. Each question was assessed via a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The averaged construct’s mean (after appropriate scale recoding) was 3.94 (SD = 0.70). The individuals who did not see these questions were coded as 0, and the mean of the entire quota sample was 2.87 (SD = 1.85).

The final operationalization, generalized collaboration, contained six items, two of which needed to be recoded. Generalized collaboration was based on items utilized by So and Brush (2007). This instrument broadly touches upon the various elements of collaboration. Each question was assessed via a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The Cronbach's Alpha value was .88; thus, the items were averaged together into one construct. The average value of the construct was 3.95 (SD = 0.77), and the average value of the construct, when coding the participants who did not see the questions as 0, was 2.88 (SD = 1.88). It was possible the three predictor variables might best operationalize collaboration as one construct. In anticipation of this consideration, all the items were averaged together (Cronbach's Alpha = .93, N = 16); the mean of the all-in construct was 2.85 (SD = 1.84). The mean for those that saw the question was 3.90 (SD = 0.69).

### ***Mediator variables.***

Continuing to the first mediator variable, a research team has generated an instrument that nicely and concisely assesses teachers' self-efficacy related to classroom data use. This 20-question instrument was discovered to assess 5 sub-concepts of data self-efficacy: 1) Identification, 2) Technology, 3) Interpretation, 4) Application, and 5) Anxiety. The research team created the five conceptualizations using one sample and validated their instrument on a holdout sample (Dunn, Airola, Lo, & Garrison, 2013). For the sake of parsimony, this dissertation did not utilize the 5 sub-conceptualizations; rather, all items were combined into one scale representing data self-efficacy. Each question was assessed via a 7-point semantic differential scale (1 = Very Much Describes Me, 7 = Does Not Describe Me at All). The 20 items used to address data self-efficacy seemed to represent the concept well; seven items were reverse coded, and all 20 items were averaged together (Cronbach's Alpha = 0.95,  $\mu$  = 3.14, SD



= 1.29). In sum, this instrument captures the nuances of self-efficacy related to classroom data use (Dunn, Airola, Lo, & Garrison, 2013).

The second variable in the serial mediation sequence, positive affect, utilized a modified form of the aforementioned 21-item Positive and Negative Affect Schedule (PANAS). Again, this tool has been frequently utilized in various strands of social scientific research (Crawford & Henry, 2004; Watson & Clark, 1999; Watson, Clark, & Tellegen, 1988). Data positive affect was well addressed by 10 items, which were averaged together (Cronbach's Alpha = 0.93,  $\mu = 4.52$ ,  $SD = 1.14$ ). While the mediated pathway does not assess negative affect, questions related to negative affect were still asked to balance the positive affect questions. The first 10 items address positive affect, while the last 11 items address negative affect (Crawford & Henry, 2004; Watson & Clark, 1999; Watson, Clark, & Tellegen, 1988). The items were assessed via a 7-point scale (1 = Strongly Disagree, 7 = Strongly Agree). The 11 negative affect items likewise hung well together (Cronbach's Alpha = 0.93). The two constructs were strongly and negatively related with one another ( $r = -0.59$ ,  $p < .001$ ), which is in accordance with the dimensional perspective of emotion (Lee & Lang, 2009; Nabi, 2010).

Demographic questions related to gender, age, years teaching, specialty, grade level, ethnicity, etc., were also asked. During the survey, all questions were randomized within the subsections. The subsections were also randomly displayed to respondents, with the exception of the screener and PD experience questions (which were always seen first, or not at all if inappropriate) and the demographic questions (which were always seen last).

### **Descriptive statistics.**

Descriptive statistics will be reported on the quota sample ( $N = 207$ ) and the overall collected sample ( $N = 268$ ) in order to demonstrate the similarities between the two datasets. However, only the quota sample will be used to test hypotheses and research questions.

### ***Quota sample.***

As per the quota sample methodology, the quota dataset mirrored the age and gender demographics of K-12 teachers in the whole of the United States. That is, 17% ( $N = 35$ ) of the sample was male, and 83% ( $N = 172$ ) was female. The average age in years was 41.46, and the average teaching tenure was 12.27 years. The sample was comprised of 22% ( $N = 46$ ) of educators in their 20s, 28% ( $N = 58$ ) of educators in their 30s, 21% ( $N = 44$ ) of educators in their 40s, and 29% ( $N = 59$ ) of educators 50-and-older. The aforementioned Table 2 displays the age and gender cross-tabulations used to generate the quota sample.

Nearly 80% ( $N = 164$ ) of the sample was comprised of teachers, while 20% ( $N = 43$ ) identified as administrator or another type of K-12 educator. The vast majority of the sample worked as an educator full time (77%,  $N = 159$ ), while the rest worked part-time or was not a current educational practitioner (23.2%,  $N = 48$ ). The sample was largely comprised of elementary school educators (64%,  $N = 131$ ), while the rest were middle school educators (15.5%,  $N = 32$ ) or high school educators (21%,  $N = 43$ ). A glitch in the first few minutes of the survey launching resulted in one participant not selecting any choice for that question. Public school educators represented the largest percentage of the sample (87%,  $N = 179$ ); 17% ( $N = 36$ ) worked at private or other types of schools. The sample was well represented by a myriad of educator types (see Table 3).

Table 3

*Quota Sample Teacher Demographics by Discipline*

Discipline	Frequency	Percent
Social Studies / History / Geography	14	6.8%
Science	12	5.8%
English / Language Arts	26	12.6%
Math	19	9.2%
Arts	7	3.4%
Special Education	33	15.9%
General Education	67	32.4%
Other	29	14%

Finally, the demographic makeup of the sample was 87% (N = 179) white and 17% (N = 28) another ethnic category. This breakout largely mirrors a recent national report published by the National Center for Education Statistics; in that report, it was published that just over 80% of K-12 teachers in the United States was white (Taie & Goldring, 2017). The aforementioned report published by the National Center for Education Information demonstrated that roughly 83% of all teachers in the United States are white (Feistritz, Griffin, & Linnajarvi, 2011). Thus, the sample utilized in this dissertation research is perhaps slightly whiter than what is found across the United States as a whole.

***Whole sample.***

For the whole sample, the age and gender characteristics of the participants did not differ materially from the quota sample. That is, 19% (N = 50) of the sample was male, and 81% (N = 218) was female. The average age in years was 40.78, and the average teaching tenure was 11.93

years. The sample was comprised of 23% (N = 62) of educators in their 20s, 31% (N = 84) of educators in their 30s, 19% (N = 50) of educators in their 40s, and 27% (N = 72) of educators 50-and-older. Table 4 displays the age and gender cross-tabulation of the whole sample's demographics.

Table 4

*Whole Sample Teacher Demographics*

Age in Years	Male		Female	
	N	Percent	N	Percent
20-29	11	4.1%	51	19%
30-39	21	7.8%	63	23.5%
40-49	9	3.4%	41	15.3%
50+	9	3.4%	63	23.5%

Nearly 79% (N = 211) of the sample was comprised of teachers, while 21% (N = 57) identified as administrator or another type of K-12 educator. The vast majority of the sample worked as an educator full time (79%, N = 212), while the rest worked part-time or was not a current educational practitioner (21%, N = 56). The sample was largely comprised of elementary school educators (63%, N = 167), while the rest were middle school educators (15%, N = 40) or high school educators (22%, N = 60). Again, the glitch in the first few minutes of the survey launching resulted in one participant not selecting any choice for that question. Public school educators represented the largest percentage of the sample (83%, N = 222); 17% (N = 46) worked at private or other types of schools. The demographic makeup of the sample was 85% (N = 229) white and 15% (N = 39) another ethnic category. Again, the larger sample represented the panoply of various teacher types (see Table 5).

Table 5

*Whole Sample Teacher Disciplines*

Discipline	Frequency	Percent
Social Studies / History / Geography	22	8.2%
Science	17	6.3%
English / Language Arts	38	14.2%
Math	22	8.2%
Arts	12	4.5%
Special Education	39	14.6%
General Education	82	30.6%
Other	36	13.4%

**Statistical testing.**

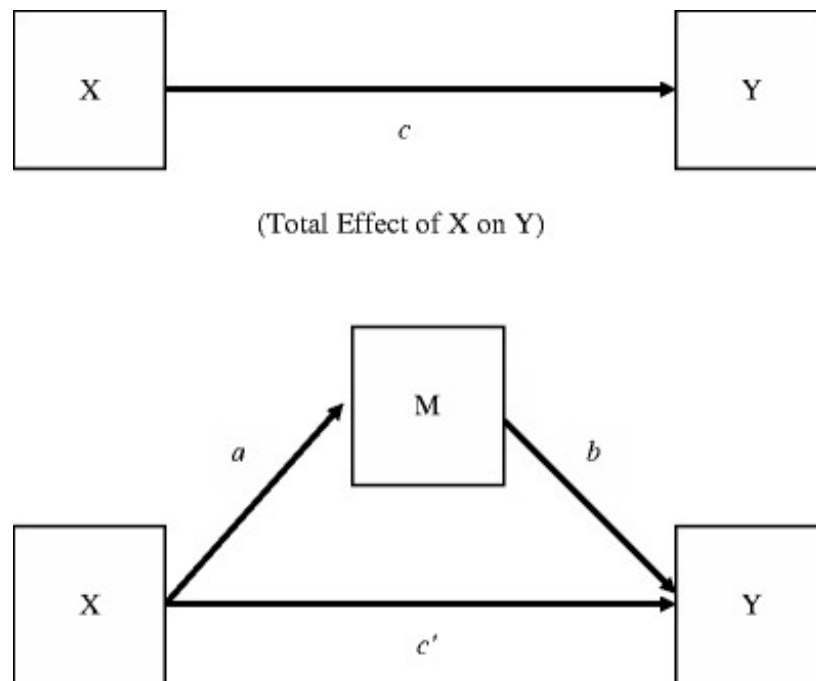
The final hypothesis and research question require a special type of statistical testing that has seen expanded use recently. This section will discuss the reasons why this type of statistical testing is being employed and some of the math behind it. Because of computational increases and more nuanced advances in statistical analyses, quantitative researchers are able to explain the psychological pathways by which predicted behaviors occur in different groups of individuals (Hayes, 2013). In general, these “why” factors are referred to as mediators and moderators (and a handful of combinations of the two), and they can be addressed via extrapolations of simple linear regression techniques by a variety of open source and enterprise software tools (SPSS, SAS, R, and Python, to name a few). Mediation and moderation both help us to understand why and how phenomena occur, whereas more traditional statistical methods just illustrate that an effect has or has not occurred. According to Hayes (2013), “These intervening variables, often called mediators, are conceptualized as the mechanism through which X Influences Y. That is,

variation in X causes variation in one or more mediators M, which in turn causes variation in Y,” (p. 7).

The following model diagram (Figure 3) demonstrates the concept behind mediation analysis, a form of which will be employed to test the final hypothesis. X, M, and Y represent the predictor variable, the mediating variable, and the outcome variable, respectively. The lowercase letters, then, simply represent the various paths between these variables.

Figure 3

*Conceptual Diagram of a Mediated Regression Model*



According to Hayes (2013), to test empirically a regression-based mediation model, one must calculate the direct and indirect effects of X on Y. A total effect of X on Y can also be computed (denoted as the  $c$  path in the diagram above); however, modern statistical approaches for mediation no longer require a significant total effect relationship as suggested by Baron and Kelly (1986), which will be discussed in more detail shortly. The two equations to calculate a simple mediation indirect effect model are:

$$\text{Indirect Effect 1: } M = i_1 + aX + e_M$$

$$\text{Indirect Effect 2: } Y = i_2 + c'X + bM + e_Y$$

In the first equation,  $i_1$  is the regression intercept,  $aX$  is the regression coefficient, and  $e_M$  is the error in estimating  $M$  (which is the mediator). In the second equation,  $i_2$  is again the regression intercept,  $c'X$  and  $bM$  are the regression coefficients, and  $e_Y$  is again the error in the estimation of  $Y$ , the outcome variable. The direct effect calculation is more complex, but it is described by the following equation.

$$\text{Direct Effect: } C' = [\hat{Y} | (X = x, M = m)] - [\hat{Y} | (X = x - 1, M = m)]$$

In this equation, the  $|$  indicates something is conditioned on, and the hat over  $Y$  indicates the value is estimated by the model. Hayes (2013) described this equation using the following terms:

A generic interpretation of the direct effect is that two cases that differ by one unit on  $X$  but are equal on  $M$  are estimated to differ by  $c'$  units on  $Y$  ... In other words, for two cases with  $M = m$  but that differ by one unit on  $X$ ,  $c'$  is the estimated value of  $Y$  for the case with  $X = x - 1$ , (Hayes, 2013, p. 91).

Finally, the total effect, or the relationship between  $X$  and  $Y$  directly, is simply calculated by the following equation:

$$\text{Total Effect: } C = [\hat{Y} | (X = x)] - [\hat{Y} | (X = x - 1)]$$

This equation is identical to the direct effect calculation, with the mediator portion excluded. In all, this final portion of the overall simple mediation calculation process is a straightforward linear function between  $X$  and  $Y$ .

In lay terms, a researcher must be able to demonstrate a significant linear relationship between  $X$  and  $M$ , a significant linear relationship between  $M$  and  $Y$ , and a diminished linear

relationship between X and Y, when controlling for M compared to the estimated coefficient between X and Y only (Baron & Kenny, 1986; Hayes, 2013).

While earlier methods for calculating a mediation model required the total effect (i.e. the unfettered relationship between X and Y, denoted as path c) to be significant (Baron & Kenny, 1986), contemporary researchers have argued such a relationship is not necessary to demonstrate evidence of mediation (Hayes, 2013; Zhao, Lynch, & Chen, 2010). It has been argued that because multiple significance tests need to be conducted to demonstrate mediation, the study may be under-powered or certain assumptions may not yet have been met in order to display statistical significance, and thus the c path will not illustrate a relationship between X and Y even though mediation may still be occurring. The alternative approach to that designed by Baron and Kenny (1986) is one where bootstrapping occurs (Hayes, 2013). Simply, bootstrapping is a method that allows for researchers to take a large quantity (usually 5,000 or more) of random samples from the collected sample with replacement (Good, 2001; Mooney & Duval, 1993). The indirect effect is estimated in each sample and then ordered from highest to lowest; a confidence interval, typically of 95%, is determined from this range of values. If the confidence interval of the indirect effect does not contain the value of 0, the indirect effect is positive or negative, and hence, is significant (Hayes, 2013). That is, we can say M mediates the relationship between X and Y. Fortunately, the SPSS macro PROCESS calculates these bootstrapped confidence intervals quickly, allowing a researcher the ability to learn if his or her hypotheses are supported by his or her data (discussed in some more detail later).

Multiple mediation occurring in serial is also a well-documented and frequently used method. According to Hayes (2013):

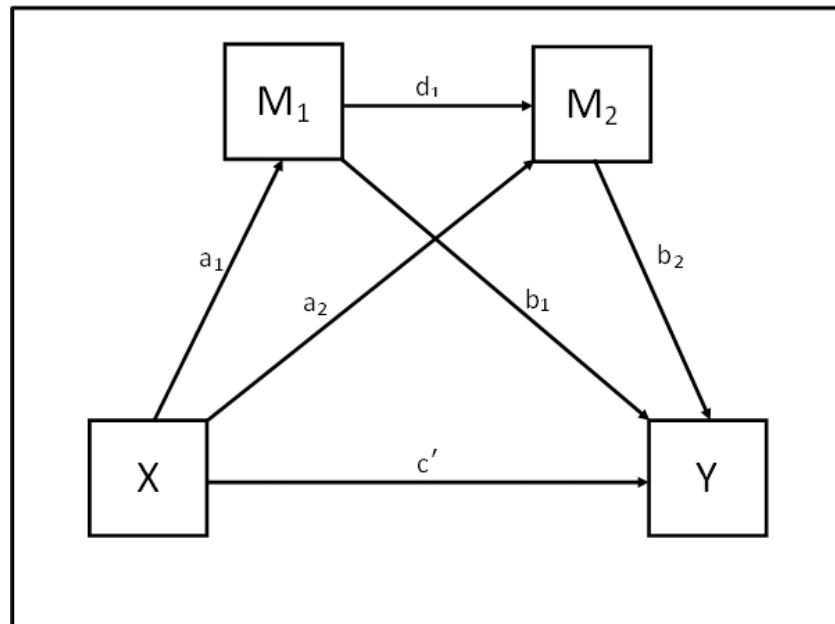


In the serial multiple mediator model, the assumption of no causal association between two or more mediators is not only relaxed – it is rejected outright a priori. The goal when an investigator estimates a serial multiple mediator model is to investigate the direct and indirect effects of X on Y while modeling a process in which X causes  $M_1$ , which in turn causes  $M_2$ , and so forth, concluding with Y as the final consequent, (p. 144).

The following diagram (Figure 4) further details the serial mediation model, which Hayes (2013) refers to as Model 6; this is the model that will be used to assess the final hypothesis. The mathematics behind this model is largely the same as the simple mediation model just discussed (Model 4).

Figure 4

*Serial Mediation Regression Model*



Moderation, which is perhaps more popularly known as an interaction effect, refers to a variable that affects the strength or direction of a predictor variable's effect at distinct levels on

an outcome variable (Baron & Kenny, 1986). Moderation variables may be qualitative, such as race or sex, or quantitative, such as age or income. According to Hayes (2013), moderation is:

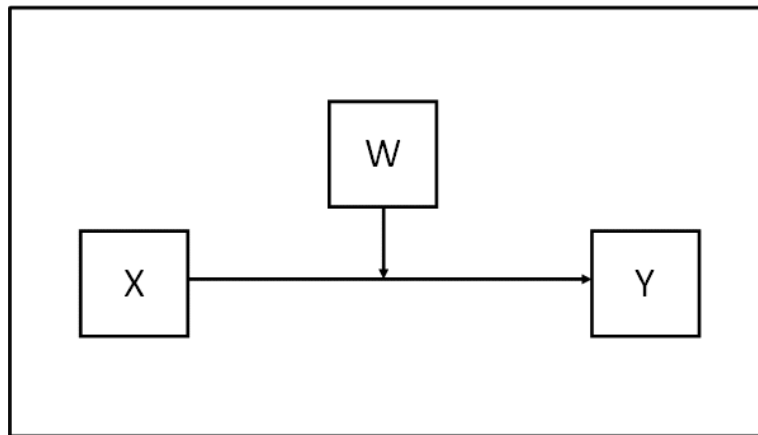
The effect of X on some variable Y is moderated by M if its size, sign, or strength depends on or can be predicted by M. In that case, M is said to be a moderator of X's effect on Y, or that M and X interact in their influence on Y. Identifying a moderator of an effect helps to establish the boundary conditions of an effect or the circumstances, stimuli, or type of people for which the effect is large versus small, present versus absent, positive versus negative... (Hayes, 2013, p. 208).

Again, this discussion will only briefly touch on some of the statistical nuance for calculating a regression-based moderation model. In short, the equation is just a slight expansion of a standard regression equation, where an interaction term is created by multiplying the independent variable and the moderator variables together, which is then added to the model equation. More specifically, the equation is as follows:

$$Y = i_1 + b_1X + b_2M + b_3XM + e_Y$$

In this model,  $i_1$  is the constant,  $e_Y$  is the error in the equation,  $b_1X$  is the value of the first independent variable,  $b_2M$  is the value of the moderator variable, and  $b_3XM$  is the multiplied product of the independent variable and the moderator variable. The following diagram (Figure 5) illustrates the conceptual relationship between the predictor, moderating, and outcome variables.

Figure 5

*Simple Moderation Regression Model*

It is not hard to see the benefits of combining both moderation and mediation into one model to test hypotheses and research questions. This combination of these two concepts, which has been called moderated mediation, mediated moderation, and more simply, conditional process modeling, allows researchers to discover the mechanisms at play between X and Y, while demonstrating that relationship is contingent upon a circumstance or context (Hayes, 2013). According to Hayes (2013), “Conditional process modeling ... is used when one’s research goal is to understand and describe the conditional nature of the mechanism or mechanisms by which a variable transmits its effect on another...” (p. 327). The mathematics behind conditional process models are essentially just the simple combination of mediation and moderation equations.

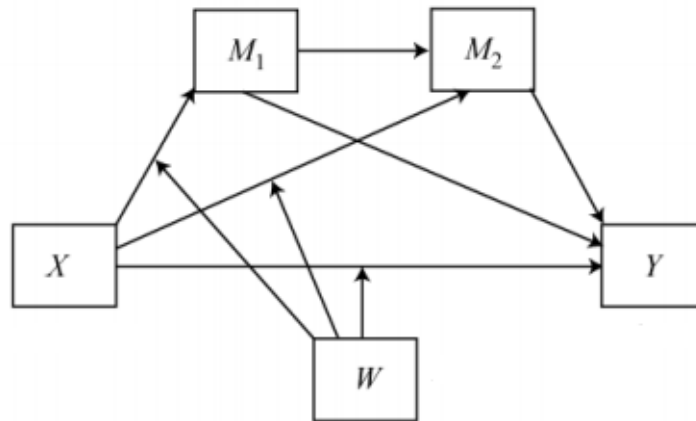
Given the discussion of regression, mediation, moderation, and conditional path analysis, all hypotheses and research questions (with the exception of H5 and RQ3) will utilize standard linear regression analyses. H5 and RQ3 require special software in order to be tested properly. Hayes (2013) created an SPSS add-on tool named PROCESS that tests for mediation and moderation, along with any number of combinations of the two. According to Hayes (2013):

PROCESS is a computational tool for path analysis-based moderation and mediation analysis as well as their integration in the form of a conditional process model. In addition to estimating unstandardized model coefficients, standard errors,  $t$  and  $p$ -values, and confidence intervals using either OLS regression (for continuous outcomes) or maximum likelihood logistic regression (for dichotomous outcomes), PROCESS generates direct and indirect effects in mediation models, conditional effects (i.e., “simple slopes”) in moderation models, and conditional indirect effects in conditional process models with a single or multiple mediators, (Hayes, 2013, p. 419).

For serial mediation analysis (H5), PROCESS Model 6 will be utilized. For the conditional path analysis (RQ3), PROCESS Model 6 with a calculated interaction term will be utilized (depicted below in Figure 6). Alternatively, PROCESS Model 85 could also be used; however, the extant literature on the application of this model is sparse. Thus, it was decided PROCESS Model 6 with the interaction term included would be sufficient, given that both models function identically to one another.

Figure 6

*Conditional Process Regression Model*



## Chapter 4: Results

Recall that one of the goals of this research was to determine if different conceptualizations and operationalizations of collaboration lent themselves well to explaining the hypothesized relationships. Fortunately, regardless of how collaborative learning is conceived (i.e. as teamwork, generalized collaboration, or shared knowledge building), the relationship was consistent across the three levels of the outcome variable. To make this determination, all subsequently reported models were run using each operationalization of collaboration as well as the all-in collaboration construct; beta coefficients and p-values did not differ in any meaningful manner. Thus, the construct representing all the predictor items related to collaborative learning was utilized. Research Questions 1 and 2 are subsequently addressed, given this finding – it seems most forms of collaborative learning within a professional development experience related to data driven decision-making will facilitate the mediated pathway. Again, the outcome variable, classroom data use, was operationalized in three ways: 1) Frequency, duration, and intensity, 2) Applied competency of classroom data use, and 3) Perceived effectiveness of classroom data use. Each model will be reported separately.

The first hypothesis proposed a positive relationship between collaborative professional development and classroom data use. For the first outcome variable, the relationship was significant ( $\beta = 0.33$ ,  $p < .001$ ); the adjusted R-Squared value was 10.4%, and the ANOVA test was statistically significant ( $F(1, 205) = 24.81$ ,  $p < .001$ ). In the second step (the model inclusive of the control variables, collaboration loses its significance ( $\beta = -0.16$ ,  $p = .53$ ), the overall model is still predictive (Adjusted R-Squared = 23.3%,  $F(7, 199) = 9.95$ ,  $p < .001$ ). For the second outcome variable, the relationship was significant ( $\beta = 0.28$ ,  $p < .001$ ); the adjusted R-Squared value was 7.3%, and the ANOVA test was statistically significant ( $F(1, 205) = 17.105$ ,  $p < .001$ ). In the second step (the model inclusive of the control variables, collaboration loses its

significance ( $\beta = 0.34$ ,  $p = .21$ ), the overall model is still predictive (Adjusted R-Squared = 13.7%,  $F(7, 199) = 5.67$ ,  $p < .001$ ). And for the final outcome variable, the relationship was significant ( $\beta = 0.26$ ,  $p < .001$ ); the adjusted R-Squared value was 6.3%, and the ANOVA test was statistically significant ( $F(1, 205) = 14.94$ ,  $p < .001$ ). In the second step (the model inclusive of the control variables), collaboration loses its significance ( $\beta = 0.32$ ,  $p = .25$ ), the overall model is still predictive (Adjusted R-Squared = 11.2%,  $F(7, 199) = 4.71$ ,  $p < .001$ ). In all, the first hypothesis is conditionally accepted – if the control variables are included, the relationship does not exist, whereas if the control variables are absent, the relationship manifests.

The second hypothesis proposed a positive relationship between collaborative PD and teacher self-efficacy related to classroom data use. The simple linear regression test provided support for the hypothesis. The adjusted R-Squared value was 7%, and the ANOVA test was statistically significant ( $F(1, 205) = 14.93$ ,  $p < .001$ ). There is a significant relationship between collaborative PD and data use self-efficacy ( $\beta = -0.18$ ,  $p < .001$ ). In other words, as the level of collaboration in PD increases, the level of teacher self-efficacy increases; because the scales of the two variables are inverses of one another, the beta coefficient is negative.

Again, when including the PD control variables, a different story is told by the data. That is, the overall model with all the control variables and the main predictor variable (collaboration) is significant ( $F(7, 199) = 4.47$ ,  $p < .001$ ). However, collaborative PD is not significant ( $\beta = 0.02$ ,  $p = .93$ ) in the model inclusive of the control variables. Interestingly, content focused PD and active learning PD are statistically significant. In other words, as content is more focused on data use, participants are more likely to develop increased feelings of data use self-efficacy; the sign is negative because the scales used for the two variables are inverses of one another ( $\beta = -0.35$ ,  $p = .02$ ). Likewise, as active learning increases, so too does teacher data use self-efficacy ( $\beta =$

0.19,  $p < .01$ ). Thus, the third hypothesis is conditionally supported by the data. When the control variables are not included in the model, collaborative professional development is a positive and significant predictor of self-efficacy. When the control variables are included, collaboration loses its significance; this phenomenon will be further discussed in the section of the analyses testing the whole mediated model.

The next hypothesis proposes a relationship between self-efficacy and positive affect. In the model absent of the control variables, data self-efficacy was significantly related to data positive affect ( $F(1, 205) = 16.65$ ,  $p < .001$ ); as self-efficacy increased, so too did positive affect ( $\beta = -0.24$ ,  $p < .001$ ); the sign is negative because the two scales are inverses of one another. When including the control variables, the hypothesized relationship is still significant ( $\beta = -0.19$ ,  $p = .001$ ). Thus, the fourth hypothesis is supported by the data.

Again, because the outcome variable was operationalized in three ways, the hypothesis regarding positive affect's response on data use need to be tested three times. In the first operationalization (Frequency, Intensity, and Duration), positive affect does significantly predict the outcome variable ( $F(1, 205) = 44.24$ , adjusted R-Square = 17%,  $p < .001$ ,  $\beta = 0.30$ ,  $p < .001$ ). In the model inclusive of the control variables, positive affect was still a significant predictor ( $F(8, 198) = 13.68$ , adjusted R-Squared, 33%,  $p < .001$ ,  $\beta = 0.24$ ,  $p < .001$ ). In the second operationalization (Applied Competency of Classroom Data Use), a similar story was told by the data, in that positive affect predicted data use by itself ( $F(1, 205) = 84.59$ , adjusted R-Square = 29%,  $p < .001$ ,  $\beta = 0.37$ ,  $p < .001$ ), and in the model inclusive of the control variables ( $F(8, 198) = 13.91$ , adjusted R-Squared = 33%,  $p < .001$ ,  $\beta = 0.32$ ,  $p < .001$ ). Finally, the third operationalization (Perceived Effectiveness of Classroom Data Use) was also similar in its story. Positive affect significantly predicted data use in isolation ( $F(1, 205) = 87.57$ , adjusted R-Square

= 29%,  $p < .001$ ,  $\beta = 1.03$ ,  $p < .001$ ) and as part of the model with the control variables included ( $F(8, 198) = 13.57$ , adjusted R-Square = 33%,  $p < .001$ ,  $\beta = 0.92$ ,  $p < .001$ ). All told, across the three operationalizations, data positive affect, regardless if the control variables were included, positively and significantly predicted classroom data use.

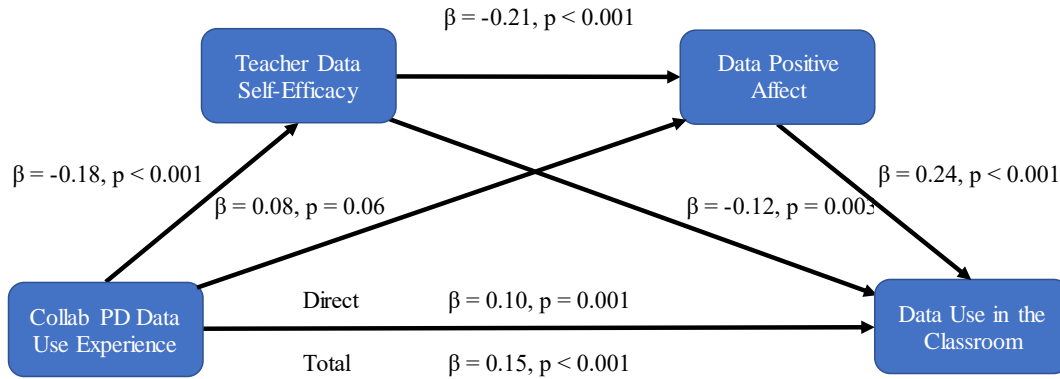
The fifth hypothesis and third research question necessitated a more robust form of statistical testing – the aforementioned conditional process modeling designed by Hayes (2013, 2018). Because three different outcome variables were operationalized to measure classroom data use, the mediated pathway will be tested three times, first in the absence of control variables, and next, including the control variables.

### **Model 1: Frequency, Duration, and Intensity**

In the first arm of the model (R-Squared = 7%,  $F(1, 205) = 14.93$ ,  $p < 0.001$ ), the predictor variable was positively and significantly related to data self-efficacy ( $\beta = 0.18$ ,  $p < .001$ ). The second step of the model was also significant (R-Squared = 9%,  $F(2, 204) = 10.27$ ,  $p < .001$ ), as self-efficacy positively predicted positive affect ( $\beta = 0.21$ ,  $p = .01$ ). Finally, increased positive affect feelings lent themselves to increased classroom data use ( $\beta = 0.24$ ,  $p < .001$ ); the overall model was significant (R-Squared = 27%,  $F(3, 203) = 25.34$ ,  $p < .001$ ). The total effect of the predictor variable on the outcome variable was positive and significant ( $\beta = 0.15$ ,  $p < .001$ ), and the direct effect of the predictor on the outcome variable, while still positive and significant, decreased in intensity ( $\beta = 0.10$ ,  $p < .001$ ) in comparison. Given the bootstrap confidence interval values of the indirect effect model do not cross 0 (LLCI = 0.00, ULCI = 0.02), there is significant evidence to suggest support for the hypothesized serial mediation model. Figure 7 displays the beta coefficients and p-values of each path.

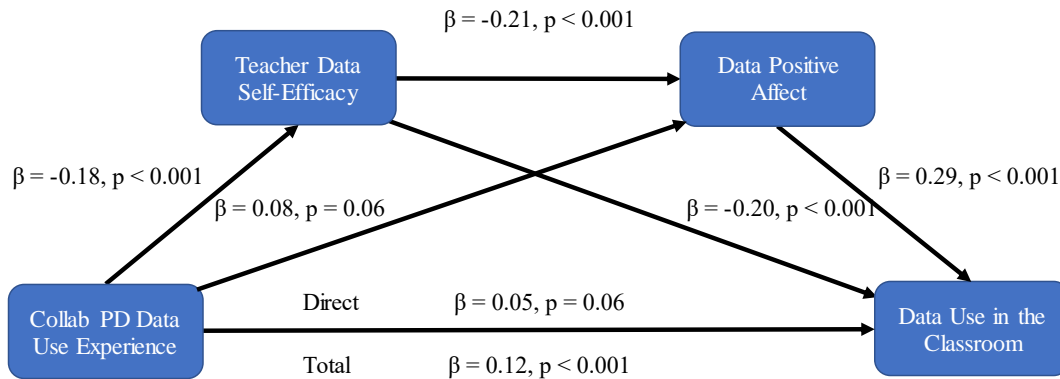


Figure 7

*Model 1: Frequency, Duration, and Intensity***Model 2: Applied Competency of Classroom Data Use**

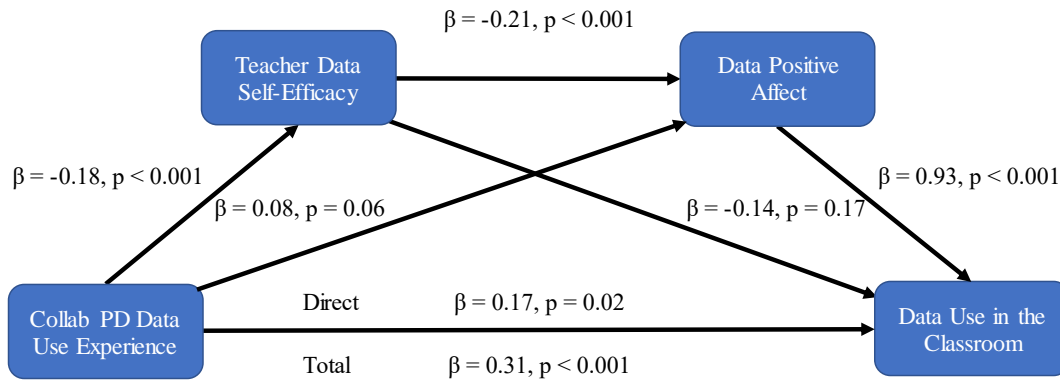
The second outcome variable conceptualized proved to be even more compelling compared to the frequency, duration, and intensity model. Given that only the outcome variable changed from the previous model to the current model, the statistics in the first two steps of this model are identical. In the direct effect model, positive affect was positively and significantly related to the outcome variable ( $\beta = 0.29, p < .001$ ); the overall model was likewise significant ( $R\text{-Squared} = 42\%, F(3, 203) = 47.88, p < .001$ ). The predictor variable in the total effect model was positive and significant ( $\beta = 0.12, p < .001$ ), while the predictor in the direct effect model lost its significance and intensity ( $\beta = 0.06, p = .06$ ). Given the bootstrap confidence interval values of the indirect effect model do not cross 0 (LLCI = 0.00, ULCI = 0.02), there is significant evidence to suggest support for the hypothesized serial mediation model. Figure 8 displays the beta coefficients and p-values of each path.

Figure 8

*Model 2: Applied Competency of Classroom Data Use***Model 3: Perceived Effectiveness of Classroom Data Use**

The final outcome variable conceptualization was also statistically significant. Again, the first two stages of the model do not differ from the previous two models. Positive affect was positively and significantly related to the outcome variable ( $\beta = 0.93, p < .001$ ); the overall model was likewise significant ( $R\text{-Squared} = 33\%$ ,  $F(3, 203) = 33.37, p < .001$ ). The predictor variable in the total effect model was positive and significant ( $\beta = 0.30, p < .001$ ), while the predictor in the direct effect model lost some of its significance and intensity ( $\beta = 0.17, p = .02$ ). Given the bootstrap confidence interval values of the indirect effect model do not cross 0 (LLCI = 0.00, ULCI = 0.03), there is, again, significant evidence to suggest support for the hypothesized serial mediation model. Figure 9 displays the beta coefficients and p-values of each path.

Figure 9

*Model 3: Perceived Effectiveness of Classroom Data Use*

The reported models were absent of any control variables being considered. Recall that there are at least five hallmarks of effective professional development (plus trait collaboration) that ought to be utilized as control variables in order to subtract their influence from the hypothesized main relationships. Therefore, the aforementioned three models were re-run with the inclusion of the six control variables. The outcome was unexpected. The total and direct effect of collaboration on data use was not statistically significant in each of the three outcome variable models; however, depending on the model, active learning and content focused factored into the results significantly. The following table (Table 6) presents the beta coefficients of collaboration, active learning, and content focused of the total and direct effect stages for the three models.

Table 6

*Total and Direct Effect Serial Mediation Regression Results with Controls*

Variable	Model 1	Model 2	Model 3
Total Effect Collaborative PD	$\beta = -0.07, p = .52$	$\beta = 0.15, p = .21$	$\beta = 0.38, p = .25$
Direct Effect Collaborative PD	$\beta = -0.18, p = .11$	$\beta = 0.17, p = .86$	$\beta = -0.05, p = .86$
Total Effect Active Learning	$\beta = -0.17, p < .001$	$\beta = -0.15, p = .002$	$\beta = -0.22, p = .09$
Direct Effect Active Learning	$\beta = -0.12, p = .004$	$\beta = -0.08, p = .05$	$\beta = -0.09, p = .42$
Total Effect Content Focused	$\beta = 0.27, p = .002$	$\beta = 0.09, p = .032$	$\beta = 0.46, p = .06$
Direct Effect Content Focused	$\beta = 0.24, p = .004$	$\beta = 0.02, p = .77$	$\beta = 0.42, p = .05$

In all three models, it is clear active learning and content focused are having suppression effects on collaboration, which is indicative of a possible moderation effect. That is, it seems that these two variables, in combination with different levels of collaboration, may best explain the hypothesized relationship. Thus, the three models were tested again, with either active learning or content focused serving as a moderating variable (thus, there were six additional total models) affecting each stage of the hypothesized relationship, and all other control variables being included.

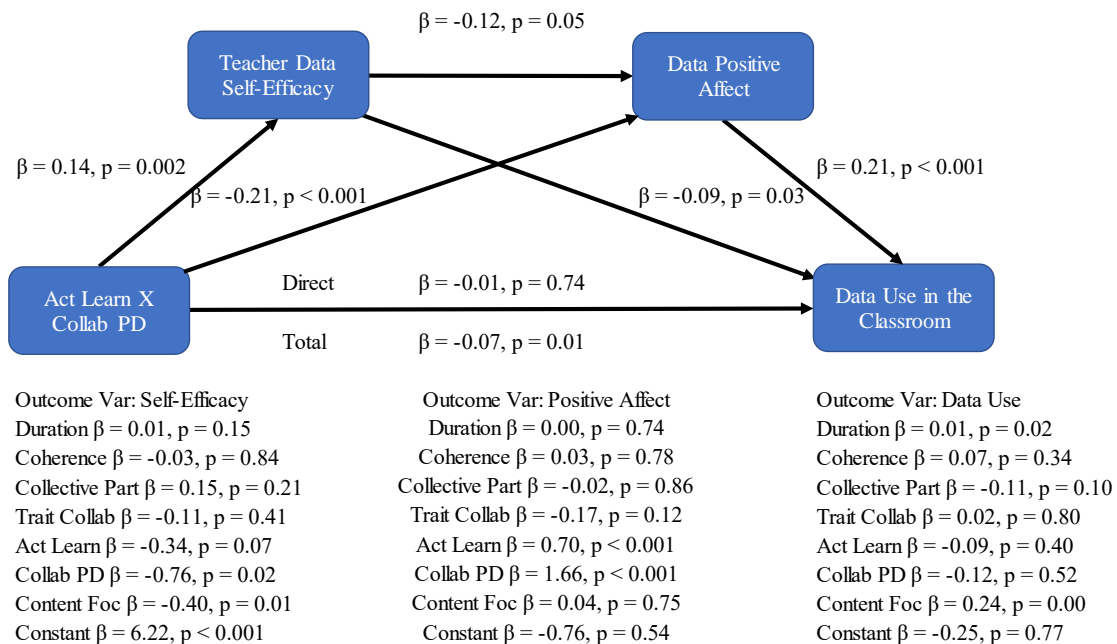
**Model 1 with an Active Learning Interaction: Frequency, Duration, and Intensity**

In the active learning moderation model with the first outcome variable, the first arm (that is, predicting self-efficacy) was significant ( $R\text{-Squared} = 18\%$ ,  $F(8, 198) = 5.38$ ,  $p < 0.001$ ). In that step, the collaborative main effect was significant ( $\beta = -0.76$ ,  $p < .02$ ), the active

learning main effect was nearing significance ( $\beta = -0.34, p < .07$ ), and the interaction term was significant ( $\beta = 0.14, p = .002$ ). In the next step, self-efficacy predicted positive affect ( $\beta = -0.12, p = .045$ ). The collaborative PD main effect was significant ( $\beta = 1.66, p < .001$ ), the active learning main effect was significant ( $\beta = 0.70, p < .001$ ), and the interaction term was significant ( $\beta = -0.21, p < .001$ ). Finally, positive affect predicted the outcome variable ( $\beta = 0.21, p < .001$ ), while collaborative learning ( $\beta = -0.12, p = .52$ ) and active learning ( $\beta = -0.09, p = .40$ ) were not significant predictors. Likewise, the interaction term also lost its significance ( $\beta = -0.01, p = .74$ ). The interaction term again subsided in its influence from the direct effect model ( $\beta = -0.01, p = .74$ ) to the total effect model ( $\beta = -0.07, p = .01$ ). Figure 10 displays the beta coefficients and p-values of each path.

Figure 10

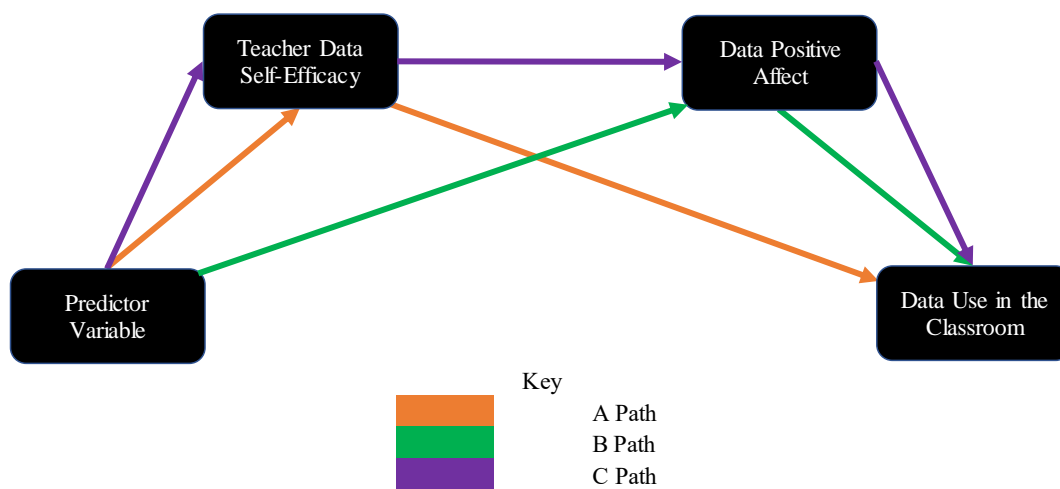
*Model 1 with an Active Learning Interaction: Frequency, Duration, and Intensity*



Taken together, there is evidence to suggest that the interaction between collaborative learning and active learning moderates the relationship among self-efficacy, positive affect, and classroom data use. The final step in determining if the overall model is significant is by examining the effect size confidence intervals for the three indirect paths (Path A being among the interaction > self-efficacy > data use, Path B being among the interaction > positive affect > data use, and Path C being among the interaction > self-efficacy > positive affect > data use). Please see Figure 11 for a graphic visualization of the various pathways. If the confidence interval of the effect size does not cross 0, the model is significant. Interestingly, Path C for the collaboration \* active learning interaction model does intersect 0, while Path A and Path B do not (Path A LLCI = -0.03, Path A ULCI = -0.00; Path B LLCI = -0.08, Path B ULCI = -0.02; Path C LLCI = -0.01, Path C ULCI = 0.00). It seems that the interaction term influences both self-efficacy and positive affect; however, it does so separately, and not in sequence. The two mediators then influence classroom data use.

Figure 11

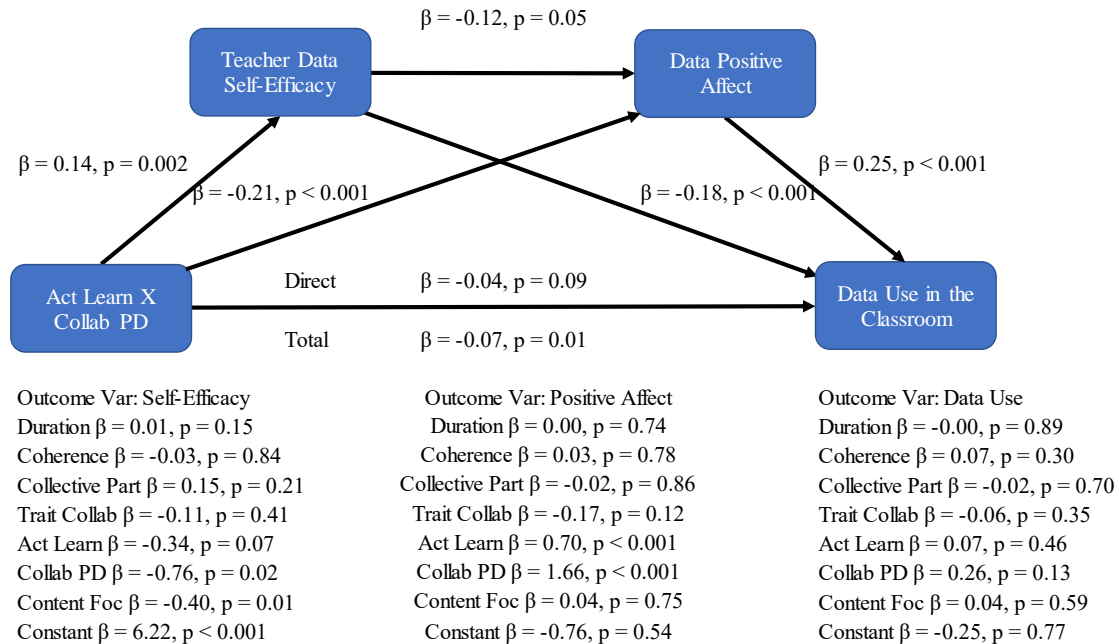
*A, B, and C Pathways of Generic Mediation Model*



**Model 2 with an Active Learning Interaction: Applied Competency of Classroom Data Use**

Given that only the outcome variable changed from the previous model to the current model, the statistics in the first two steps of this model are identical. In the direct effect model, positive affect was positively and significantly related to the outcome variable ( $\beta = 0.25$ ,  $p < .001$ ); the overall model was likewise significant ( $R\text{-Squared} = 45\%$ ,  $F(10, 196) = 15.95$ ,  $p < .001$ ). Collaborative learning was not significant ( $\beta = .026$ ,  $p = .13$ ), nor was active learning ( $\beta = 0.7$ ,  $p = .46$ ) and the interaction effect ( $\beta = -0.04$ ,  $p = .09$ ). The interaction term again subsided in its influence from the direct effect model ( $\beta = -0.04$ ,  $p = .09$ ) to the total effect model ( $\beta = -0.12$ ,  $p < .001$ ). The final step in determining if the overall model is significant is by examining the effect size confidence intervals for the three indirect paths. Path C for the collaboration \* active learning interaction model does intersect 0, while Path A and Path B do not (Path A LLCI = -0.05, Path A ULCI = -0.01; Path B LLCI = -0.08, Path B ULCI = -0.02; Path C LLCI = -0.01, Path C ULCI = 0.00). Again, it seems that the interaction term influences both self-efficacy and positive affect; however, it does so separately, and not in sequence. The two mediators then influence classroom data use. Figure 12 displays the beta coefficients and p-values of each path.

Figure 12

*Model 2 with an Active Learning Interaction: Applied Competency of Classroom Data Use***Model 3 with an Active Learning Interaction: Perceived Effectiveness of Classroom Data****Use**

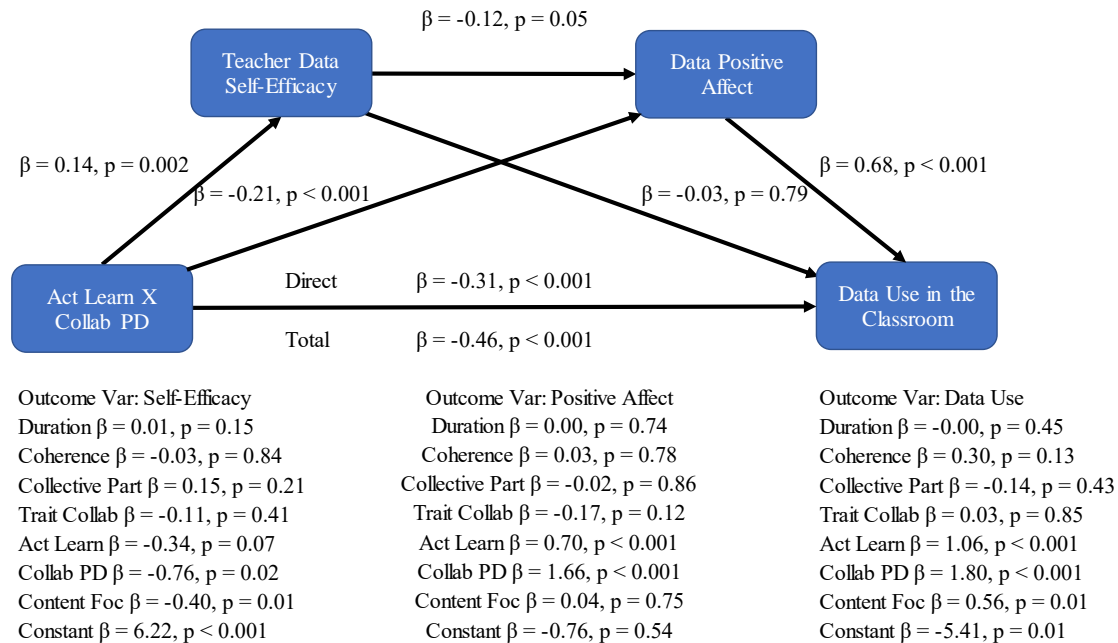
Again, given that only the outcome variable changed from the previous model to the current model, the statistics in the first two steps of this model are identical. In the direct effect model, positive affect was positively and significantly related to the outcome variable ( $\beta = 0.68, p < .001$ ); the overall model was likewise significant ( $R\text{-Squared} = 42\%, F(10, 196) = 14.30, p < .001$ ). Collaborative learning was significant ( $\beta = 1.80, p = .13$ ), as was active learning ( $\beta = 1.06, p < .001$ ) and the interaction ( $\beta = -0.31, p < .001$ ). The interaction term again subsided in its influence from the direct effect model ( $\beta = -0.31, p < .001$ ) to the total effect model ( $\beta = -0.46, p < .001$ ). The final step in determining if the overall model is significant is by examining the effect size confidence intervals for the three indirect paths. Paths A and C for the collaboration \* active learning interaction model do intersect 0, while Path B does not (Path A LLCI = -0.04,



Path A ULCI = 0.21; Path B LLCI = -0.22, Path B ULCI = -0.08; Path C LLCI = -0.03, Path C ULCI = 0.00). It seems that the interaction term only influences positive affect, at least for this outcome variable. Figure 13 displays the beta coefficients and p-values of each path.

Figure 13

*Model 3 with an Active Learning Interaction: Perceived Effectiveness of Classroom Data Use*



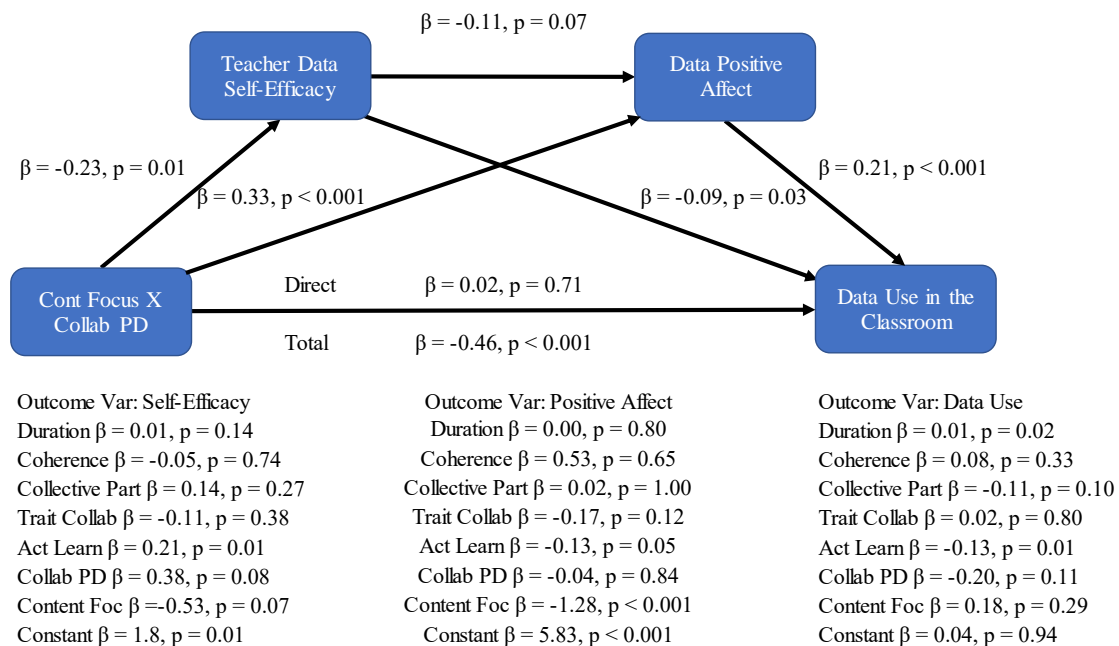
**Model 1 with a Content Focused Interaction: Frequency, Duration, and Intensity**

In the content focused moderation model with the first outcome variable, the first arm (that is, predicting self-efficacy) was significant ( $R\text{-Squared} = 19\%$ ,  $F(8, 198) = 5.74, p < 0.001$ ). In that step, the collaborative main effect was nearing significance ( $\beta = 0.38, p < .08$ ), the content focused main effect was nearing significance ( $\beta = 0.52, p = .08$ ), and the interaction term was significant ( $\beta = -0.23, p < .001$ ). In the next step, self-efficacy predicted positive affect ( $\beta = -0.11, p = .07$ ), though not significantly. The collaborative PD main effect was not significant ( $\beta = -0.04, p = .84$ ), the content focused main effect was significant ( $\beta = -1.28, p < .001$ ), and the interaction term was significant ( $\beta = 0.33, p < .001$ ). Finally, positive affect predicted the

outcome variable ( $\beta = 0.21, p < .001$ ), while collaborative learning ( $\beta = -0.20, p = .11$ ) and content focused ( $\beta = 0.18, p = .29$ ) did not. Likewise, the interaction term also lost its significance ( $\beta = 0.02, p = .71$ ). The interaction term again subsided in its influence from the direct effect model ( $\beta = 0.02, p = .71$ ) to the total effect model ( $\beta = 0.11, p = .01$ ). The final step in determining if the overall model is significant is by examining the effect size confidence intervals for the three indirect paths. Path C for the collaboration \* active learning interaction model does intersect 0, while Path A and Path B do not (Path A LLCI = 0.00, Path A ULCI = -0.05; Path B LLCI = 0.03, Path B ULCI = 0.12; Path C LLCI = -0.00, Path C ULCI = 0.01). It seems that the interaction term influences both self-efficacy and positive affect; however, it does so separately, and not in sequence. The two mediators then influence classroom data use. Figure 14 displays the beta coefficients and p-values of each path.

Figure 14

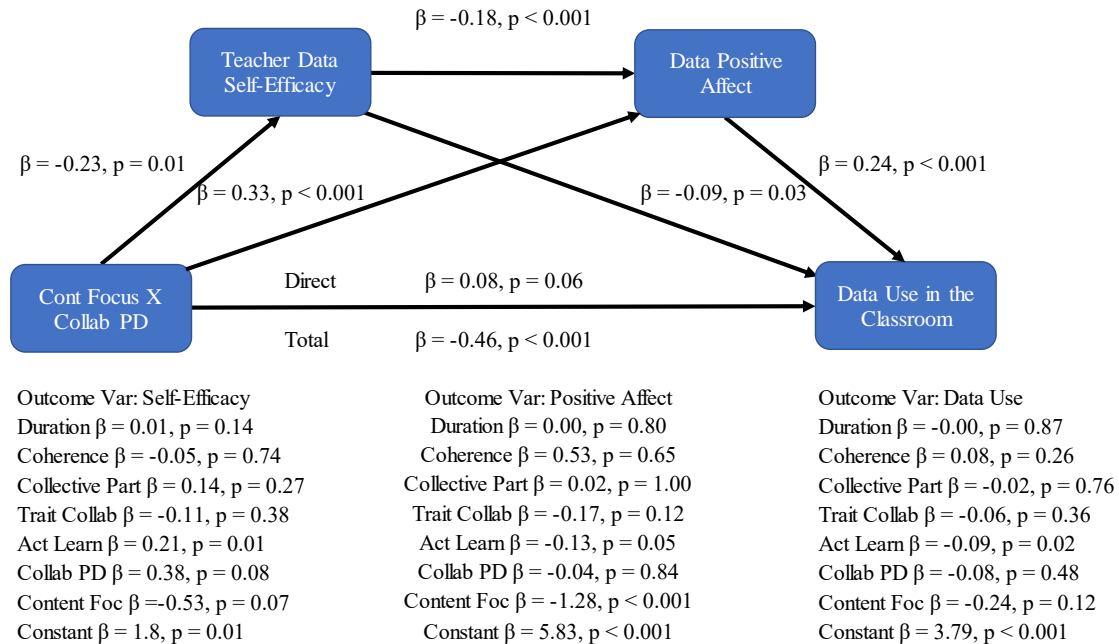
*Model 1 with a Content Focused Interaction: Frequency, Duration, and Intensity*



**Model 2 with a Content Focused Interaction: Applied Competency of Classroom Data Use**

Given that only the outcome variable changed from the previous model to the current model, the statistics in the first two steps of this model are identical. In the direct effect model, positive affect was positively and significantly related to the outcome variable ( $\beta = 0.24$ ,  $p < .001$ ); the overall model was likewise significant ( $R\text{-Squared} = 45\%$ ,  $F(10, 196) = 16.10$ ,  $p < .001$ ). Collaborative learning was not significant ( $\beta = -0.08$ ,  $p = .48$ ), nor was content focused ( $\beta = -0.24$ ,  $p = .12$ ) or the interaction term ( $\beta = 0.07$ ,  $p = .06$ ). The interaction term again subsided in its influence from the direct effect model ( $\beta = 0.07$ ,  $p = .06$ ) to the total effect model ( $\beta = 0.20$ ,  $p < .001$ ). The final step in determining if the overall model is significant is by examining the effect size confidence intervals for the three indirect paths. Path C for the collaboration \* active learning interaction model does intersect 0, while Path A and Path B do not (Path A LLCI = 0.08, Path A ULCI = 0.19; Path B LLCI = 0.04, Path B ULCI = 0.013; Path C LLCI = -0.00, Path C ULCI = 0.02). It seems that the interaction term influences both self-efficacy and positive affect; however, it does so separately, and not in sequence. The two mediators then influence classroom data use. Figure 15 displays the beta coefficients and p-values of each path.

Figure 15

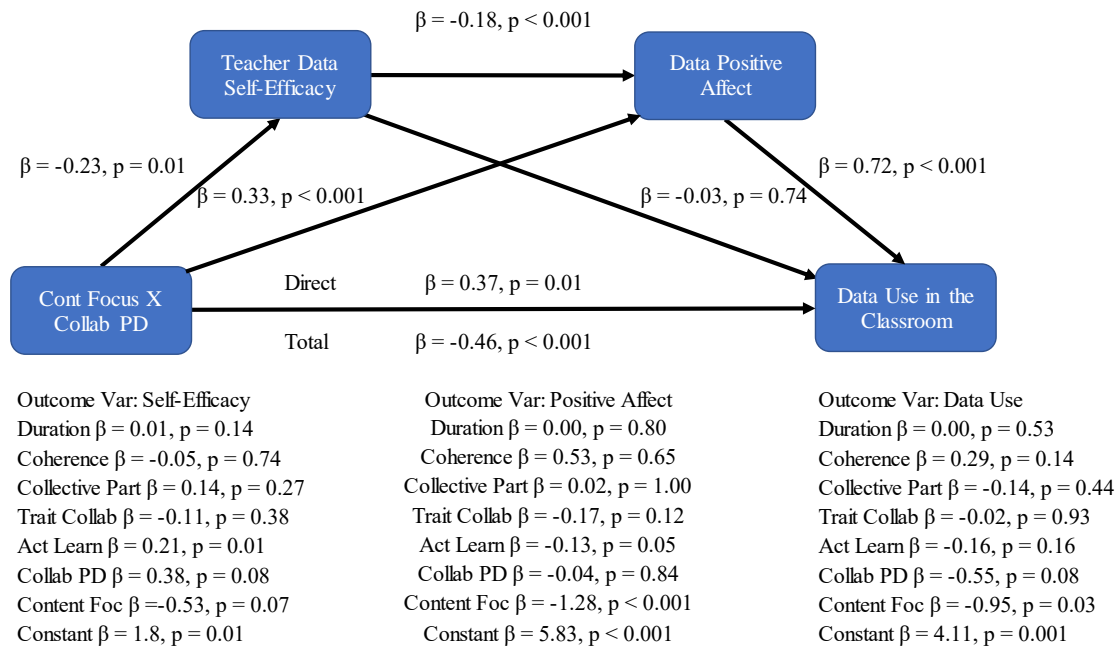
*Model 2 with a Content Focused Interaction: Applied Competency of Classroom Data Use***Model 3 with a Content Focused Interaction: Perceived Effectiveness of Classroom Data****Use**

Again, given that only the outcome variable changed from the previous model to the current model, the statistics in the first two steps of this model are identical. In the direct effect model, positive affect was positively and significantly related to the outcome variable ( $\beta = 0.72, p < .001$ ); the overall model was likewise significant ( $R\text{-Squared} = 40\%, F(10, 196) = 12.85, p < .001$ ). Collaborative learning was not significant ( $\beta = -0.55, p = .08$ ); however, content focused was significant ( $\beta = -0.95, p = .03$ ), as was the interaction ( $\beta = 0.37, p < .001$ ). The interaction term again subsided in its influence from the direct effect model ( $\beta = 0.37, p < .001$ ) to the total effect model ( $\beta = 0.64, p < .001$ ). Paths A and C for the collaboration \* active learning interaction model do intersect 0, while Path B does not (Path A LLCI = -0.04, Path A ULCI = 0.06; Path B LLCI = 0.13, Path B ULCI = 0.38; Path C LLCI = -0.00, Path C ULCI = 0.05).

Based on these confidence intervals, the interaction term leads to positive affect, which in turn leads to classroom data use. Figure 16 displays the beta coefficients and p-values of each path.

Figure 16

*Model 3 with a Content Focused Interaction: Perceived Effectiveness of Classroom Data Use*



### Age as a Possible Moderator

The final research question positioned the hypothesized model in the context of age. Specifically, it asked if age moderated the effect. An age interaction term was calculated by multiplying age by collaborative learning predictor variable. In each of the three iterations of the path analysis, the interaction term was not significant with the exclusion and inclusion of the control variables. Table 7 displays the beta coefficients of the interaction term in the direct effect and total effect models. Given the lack of significance of the conditional path analyses, it can be inferred that age does not moderate the relationship between collaborative learning and classroom data use (by way of self-efficacy and positive affect).

Table 7

*Age as a Possible Moderator*

Collaborative PD * Age	Model 1	Model 2	Model 3
Total Effect No Controls	$\beta = -0.00, p = .60$	$\beta = -0.00, p = .14$	$\beta = -0.01, p = .04$
Direct Effect No Controls	$\beta = 0.00, p = .75$	$\beta = -0.00, p = .65$	$\beta = -0.01, p = .21$
Total Effect with Controls	$\beta = -0.00, p = .74$	$\beta = -0.00, p = .18$	$\beta = -0.01, p = .03$
Direct Effect with Controls	$\beta = -0.00, p = .68$	$\beta = -0.00, p = .70$	$\beta = -0.01, p = .16$

Before moving onto the final chapter, the following table illustrates which hypotheses were supported and the way in which each research question was answered, based on if the control variables were excluded or included (see Table 8).

Table 8

*Results of Hypotheses and Research Questions*

Hypothesis / Research Question	Without Controls	With Controls
H1	Supported	Not Supported
RQ1	No Difference	No Difference
RQ2	No Difference	No Difference
H2	Supported	Not Supported
H3	Supported	Supported
H4	Supported	Supported
H5	Supported	Not Supported
RQ3	No Moderation	No Moderation

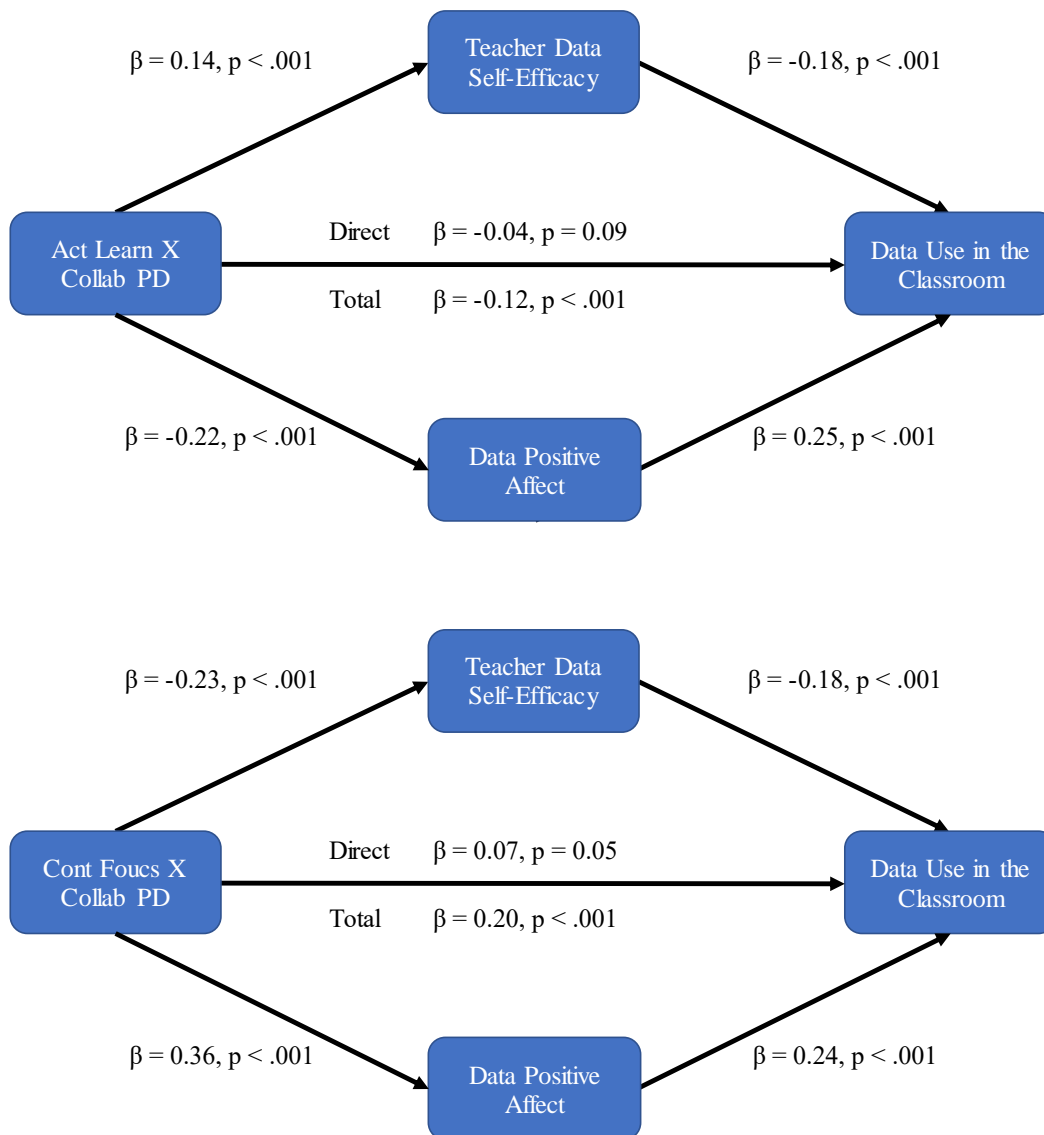
## Chapter 5: Conclusions and Implications

### Summary

The analyses of the data presented in the previous section provide a nuanced and even a possibly contradictory story. On the one hand, when only the primary predictor variable (collaborative professional development) and two mediators in sequence are included in the models (data self-efficacy and data positive affect), the hypotheses are well supported. That is, the hypothesized model predicts the three operationalizations of teachers using student data to make classroom decisions. Age did not seem to play a moderating role in that relationship. However, when running the hypothesized model with the inclusion of the control variables, collaboration loses its influence, while active learning and content focus bubble to the top as predictors of the outcome variable operationalizations. This indicates the two control variables were having a suppressing effect on collaboration. In other words, these variables were separately or in combination moderating the hypothesized relationship. To test this assumption, two higher order interaction variables were created by multiplying the collaboration predictor variable with the two control variables having the suppression effect. The two interaction terms positively predicted the majority of the outcome variable operationalizations – but not in sequence. Rather, it seems the interaction variables positively predicted self-efficacy and positive affect (which then predicted the outcome variables); however, this flows through self-efficacy and positive affect separately. In essence, the below relationship is occurring when including the interaction effect variables (see figure 17, note that only the second outcome variable models are reported, given the lack of differences regarding the three outcome variable models).

Figure 17

*Parallel Mediation Regression Models (Outcome Variable 2 Only Reported)*



It should be noted that given the two higher order interactions proved to be significant paths, it follows that a triple interaction effect might be significant. That is, the product of high collaboration, high active learning, and high content focus, leads to high data self-efficacy,



which leads to high data positive affect, and which then leads to high classroom data use.

Unfortunately, this simple explanation did not pan out when considering the various complexities of the data analysis tools.

To test for this as a possible explanation, the triple interaction effect was computed (collaboration \* active learning \* content focused) and was inserted into the model as the primary predictor. The three lower order interactions were also included, as were the main effects and control variables. The triple interaction effect was not significant in any of the iterations (with the control variables included, and with the control variables excluded). It is probable that this phenomenon is ill-suited to be tested by the data afforded by the sample size. That is, when research gets into a three-level interaction term, a much larger sample size is needed for all the lower level interactions, main effects, and control variables to be considered properly. Indeed, according to G\*Power, a model with a small-to-medium effect size with 10 predictor variables would necessitate a sample size of over 325 teachers, which is beyond the scope of this research. Moreover, three-level interactions (and beyond) are more frequently found in experimental studies, where three independent conditions can carefully be manipulated. This study's scope did not provide those affordances; thus, the content focused \* collaboration interaction term and the active learning \* collaboration interaction term will be discussed separately from one another in this discussion section.

It is plausible to assume that collaboration and active learning, and collaboration and content focus do not operate in isolation to one another; rather, they seem to be variables that fuel one another. Recall the primary hypothesized model predicted the following relationship: Collaboration > Self-Efficacy > Positive Affect > Data Use. Given the analyses of this dissertation, in isolation of extant control variables, this relationship does occur as predicted. But

when collaborative professional development experiences are married with active learning professional development experiences, that relationship breaks down into a parallel mediation model. In other words, self-efficacy and positive affect no longer operate in sequence, but are separate of one another (for two of the three outcome variable models, at least). The same is true of collaborative professional development experiences that are high in focused content (again, for at least for two of the three outcome variable models), which seem to produce teachers that exhibit high classroom data use behaviors.

What is interesting is that, as previously mentioned, there exists a significant body of literature indicating self-efficacy is a predictor of positive affect (Bandura, 1997; Caprara, Steca, Gerbino, Paciello, & Vecchio, 2006; Treasure, Monson, & Lox, 1996). After all, it makes sense that if one feels he or she has the ability to accomplish a task, then he or she is likely to feel better about engaging in the task. But it seems these two interaction terms affect the two mediators in parallel, and not in serial. In the methodology section, serial mediation was discussed; however, given that parallel mediation seems to be at play in these relationships, it will briefly be discussed here.

The parallel mediation model is most like the simple mediation model, where two or more mediators, simultaneously, explain the relationship between two variables (Hayes, 2013). These variables typically are correlated with one another, either positively or negatively. When a parallel mediation model is calculated, it is assumed that each mediating variable explains a portion of the relationship between the predictor and outcome variables (Hayes, 2013). Typically, most studies only have enough statistical power for testing two or three parallel mediating variables (Calogero & Jot, 2011; Duffy, Allen, & Dik, 2011). However, there are

examples of studies that employ four or more mediating variables operating simultaneously (Alvarez & Juang, 2010; Brandt & Reyna, 2010; Fonner & Roloff, 2010).

With that being said, it is interesting that use of the interaction variables degrades the serial mediation models into parallel mediation models. It certainly is possible this study's sample size does not afford it enough statistical power to detect a nuanced serial mediation model. However, given the high levels of significance between the two mediators and the three outcome variables in the interaction models, it seems that the causal relationship from self-efficacy to positive affect, at least in the effect on classroom data use of teachers, does not apply in this setting.

It is also possible that the five hallmarks of effective professional development should not serve as control variables when studying the effects of a single effective element in an experience, unless that study is experimental in nature. Recall that this study did not manipulate the conditions in which teachers engaged in the various types of professional development experiences. Utilizing the five hallmarks as control variables in service of a highly controlled experimental study may prove to be more appropriate, given the nature of the carefully manipulated conditions experimental design participants are exposed. Indeed, the five hallmarks were, more or less, all highly and significantly correlated with one another. Detangling the effects of one control variable from another in a cross-sectional data collection technique (albeit one that does rely on the quota sample methodology) may be very difficult when conditions are not precisely manipulated, and variables are highly correlated with one another. In other words, multicollinearity may be a culprit that is confounding the relationship between collaboration and the mediator / outcome variables, when including all the control variables in the model. Table 10 displays the bivariate correlation values among the five hallmarks and trait collaboration (the

sixth control variable (see Table 9) to demonstrate the high interrelationships these variables all share.

Table 9

*Bivariate Correlation Statistics (Represented as R-Values)*

	Collab	Duratn	Cont Focus	Active Learn	Coherence	Coll Particip	Trait Collab
Collab	1	0.06*	0.45**	-0.40**	0.45**	0.29**	0.48**
Duratn		1	0.27**	-0.32**	0.15*	0.20**	0.14*
Cont Focus			1	-0.80**	0.85**	0.84**	0.84**
Active Learn				1	-0.78**	-0.78**	-0.78**
Coherence					1	0.93**	0.86**
Coll Particip						1	0.85**
Trait Collab							1

Note: \*  $p < .05$ , \*\*  $p < .01$

Moreover, the standard rule of thumb is that when a variable exhibits a variance inflation factor (VIF) value that is greater than 10 in a model, there is significant evidence of multicollinearity with at least one other variable (O'Brien, 2007). In each iteration of the various models, collaboration exhibited a VIF value of at least 17 when the control variables were included. It has been argued that variables which exhibit VIF values greater than 10 or larger should not be removed wholesale from a model (O'Brien, 2007). But these variables do warrant additional conceptual and theoretical discussion. Therefore, there is inconclusive evidence these variables may not uniquely operationalize a concept.

Regardless, assuming these concepts are sufficiently different from one another, understanding these two interaction effects requires discussion. Why these phenomena are occurring may be because of the unique interplay between active learning and collaboration, and focused content and collaboration. The active learning interaction will be discussed first. Recall that active learning has been defined as "... opportunities for teachers to become actively engaged in the meaningful analysis of teaching and learning, for example, by reviewing student work or obtaining feedback on their teaching..." (Desimone, Porter, Garet, Yoon, & Birman, 2002, p. 83). What is key within this definition is that active learning is inherently a collaborative experience. For example, an active learning experience could be a group of teachers providing demonstrations to one another, then talking as a group to provide feedback and advice to learn what worked and what could be improved. Those discussions, then, are exemplifications of collaborative learning – that is, teachers working together to learn a new skill. It seems, then, that when a professional development experience incorporates active learning, it, by definition, is also incorporating collaboration. The inverse of that is also true. Therefore, multicollinearity was most likely the culprit on the suppression effect of active learning on collaboration.

The content focused by collaboration interaction set of models needs a bit more nuance and development compared to the active learning by collaboration interaction models. This is namely because professional development that is content focused need not be collaborative in nature (whereas there is a significant amount of conceptual overlap between active learning and collaboration). Recall that a content focused professional development experience is one where only a primary topic or concept is explored, studied, and learned. A content focused professional development experience is akin to a deep dive into material that will ultimately help the teacher adopt a new behavior in aid to his or her teaching endeavors (Desimone, 2009). It does not seem

odd that a professional development experience related to data use that is high in a data content focus and high in collaborative activities will result in increased data use. What is odd is that the two hallmarks of professional development are intrinsically different from one another. That is, these hallmarks are not like one another, whereas active learning and collaboration are like one another.

It could be that in order for a data use professional development experience to be successful, it requires both high levels of collaboration and focused content. Because active learning and collaboration are sufficiently comparable concepts, active learning may be suppressing the effect of collaboration in ways wholly different from content focus. If this is the case, the ramifications for professional development providers, at least in terms of professional development geared towards classroom data use, could be large. In other words, collaboration itself does not work alone for teachers to develop data use skills; the experience must also include high levels of focused content. When the two concepts are present in sufficiently high levels, the professional development experience is most likely to be perceived as successful by participants.

A data use program that would satisfy this condition would look the way it sounds. The entire professional development experience would be dedicated to classroom data use, and all activities would require varying levels of collaboration. This could include teachers writing a lesson plan together based on their conclusions from a joint analysis of some set of student data. Another activity that would satisfy this consideration could be one where teachers use separate but complementary bits of information to collectively generate code that would allow them to query their district's student databases. In either example, all activities would be collaborative and focused wholly on using student data in the classroom. Indeed, this dissertation's survey also

contained an optional open-ended question at the end, asking teachers if they wanted to provide any additional thoughts. Two of these qualitative responses seem to validate the above assertion (that is, professional development that is focused on student data use and is collaborative may result in successful use of student data).

One female teacher in the 20-29 age bracket wrote:

We track student data weekly and group changes can occur based on those results. As a school we assess data during PD monthly (if not more). We have built in intervention time to our schedule to help struggling students. Weekly data is looked at by each teacher, grade level, manager and principal.

Another female teacher in the 30-39 age bracket wrote:

I feel that my district is great at emphasizing data and how to interpret it. When I started teaching, this was one area that I knew nothing about straight out of college. I have learned a lot about this working with colleagues from various subject areas and attending professional development opportunities. I also am thankful that my school makes all subject areas feel included in these trainings, even those of us in Health and PE.

The second appendix includes to corpus of the open-ended responses, broken out by age and gender (see Appendix 2).

## **Limitations**

As previously mentioned, the purposes of moderation and mediation are to understand the mechanisms and different levels of effects between two variables. Ideally, these relationships would be examined under carefully controlled, experimental settings, so we could definitively state that the proposed mediators or moderators were causally related. Absent of an experimental design, the second most ideal method would be a nationally representative sample of a population of interest. Unfortunately, conducting an experiment, even a quasi-experiment, would

require a researcher to spend significant time, money, and resources on developing an intervention plan so suitable group comparison could occur. Similarly, convening a nationally representative sample is also prohibitively expensive, and perhaps, even impossible, assuming the population is not completely known.

This leads social science and education researchers then to draw upon non-random, convenience sampling, like what was convened in this dissertation, in order to conduct studies. Again, recall that convenience sampling is defined as “... a type of nonprobability or nonrandom sampling where members of the target population meet certain practical criteria, such as ease of accessibility, geographical proximity, availability at any given time, or the willingness to participate are included for the purpose of the study,” (Etikan, Musa, & Alkassim, 2016, p. 2). Not surprisingly, there are inherent issues associated with non-random surveying to collect data. First, it is assumed that the population is homogenous, and taking a convenience sample of this group would yield results that were no different had the researcher randomly sampled from the population. Obviously, this assumption is almost never observed; thus, the data generated from a convenience sample will be biased in some way. It is essential that a researcher using convenience sampling acknowledges this problem in any write-up of the results. Moreover, researchers need to provide exhaustive descriptive statistics of the sampled group so readers understand how similar or dissimilar are the participants to the general population of interest (Etikan, Musa, & Alkassim, 2016).

In a study of teachers’ experiences with professional development sessions related to classroom data use, anything other than a convenience sample would be impossible. First, the whole population is unknown; that is, there is no central repository of data that shows every teacher that has attended at least one professional development experience on data use. Because



the education system in the United States is decentralized, it would require a researcher to contact every school in the country, public and private, and request that data from all the principals or school leaders just to identify the population. From there, a random sampling of all teachers who have met the study's criteria could be convened. Obviously, this is not only financially unfeasible and a durational nightmare, but it also assumes that all principals would willingly provide that information in a timely and complete manner. Given this inherent problem of identifying the whole population to randomly sample from it, a convenience sample is simply the only alternative solution.

Fortunately, convenience sampling's limitations may be somewhat mitigated by creative solutions. One of the goals of all scientific research is that researchers' claims and results are reproducible (Mesirov, 2010). Indeed, had the early astronomers not taken notes and not provided documentation for the predicted planetary movements (i.e. their work not being reproducible), Einstein's Theory of Relativity might have been delayed, and our understanding of the universe could have been diminished compared to its current state. Thus, conducting pilot studies or multiple studies using convenience sampling techniques, and assuming the results are similar across the various studies, decreases some of the bias with that type of sampling. In other words, when results across two or more studies are similar, we can be more confident that: 1) Our samples do match the unknown population, or 2) The phenomena we are observing are robust enough that random sampling is not necessary. The aforementioned pilot study was conducted to address this, and the data generated from the main study reproduces some of the results on a larger sample.

Another workaround to the limitations posed by a convenience sample is by recruiting and collecting data on hundreds of participants. When a sample, even a convenience sample, is

sufficiently large, the sampling error is decreased, allowing conclusions to be more generalizable. In short, sampling error “is defined as the deviation of a sample from the population ... from which it was taken,” (Regev, et al., 2002, p. 2615). In other words, any sample will be different to some extent compared to the whole population regardless of sampling methodology a researcher uses. However, when a sample increases in size, it will look more and more similar to the overall population. While a sample of 207 participants does not constitute a huge sample size, it is sufficiently large, which helps ensure the sample is somewhat representative of the population.

The final way in which the limitations associated with convenience sampling can be somewhat mitigated is through using a quota sample. This study employed that technique. Recall quota sampling is a purposive sampling technique that allows researchers to conveniently collect data from participants, but ensures that the sample closely mirrors a larger population (Acharya, Prakash, Saxena, & Nigam, 2013; Cumming, 1990). In the context of this study, the sample was constructed to match the age and gender demographics of educators in the United States. While the sample used in this dissertation is not nationally representative, it still is representative of the demographic makeup of teachers in this country.

Another limitation of convenience sampling is that it disallows causal claims to be made. In his seminal work, Hayes (2013) discussed the concept of conducting mediation and moderation analyses on survey data. Recall that ultimately, the goal of a mediation analysis is to explain causal mechanisms that link two variables. However, when data are collected via a convenience sample, we can no longer say the mechanisms being explored are truly causal. Hayes (2013) argued that mediation and moderation testing ought to still be conducted on a dataset even when that data do not lend themselves to making causal claims. Data will always be

flawed to some extent; it is the researcher's job to discuss the data's limitations and then to interpret the conclusions to the best of his or her ability. Hayes (2013) wrote, "So long as we couch our causal claims with the required cautions and caveats given the nature of the data available, we can apply any mathematical method we want to understand and model relationships between variables," (p. 89). Therefore, it is important to indicate that this study is correlational in nature, and not causal.

Finally, and to what was previously alluded, there may be some doubt regarding the appropriateness of the five hallmarks serving as effective control variables. Because these five variables were not able to be manipulated experimentally in the present study, it leads to some questions as to whether they ought to behave as appropriate control variables. And indeed, these variables were all highly correlated with one another, and exhibited high variance inflation factors (VIF) values in each iteration of the models. It is possible that it is not appropriate, at least in correlational research, to utilize variables that are so highly correlated with one another as control variables in a study. If these variables were manipulated via experimental conditions, then more conclusive statements regarding their effects could be stated. As it is presently, though, this research design disallows for conclusive and causal claims to be made regarding the appropriateness of this study's control variables.

## **Conclusions**

Not all professional development is effective; likewise, even effectively designed professional development programs may differ in the mechanisms that drive the relationship between content and successful acquisition and use of a behavior. In other words, different mediating and moderating relationships may drive the content of various professional development programs. In the context of a professional development program on classroom data

use, it seems that highly collaborative experiences on the topic are likely to lead to increased levels of self-efficacy, given that using data requires creative thinking skills, and collaboration increases the likelihood of creative solutions. When teachers exhibit heightened levels of self-efficacy, they then are likely to have a happier disposition related to using data. Finally, when teachers feel positively about using data, they are more likely to actually use data in their classrooms in a successful manner. However, it is also possible the relationship led by collaborative learning is contingent upon either A) high levels of active learning, B) high levels of focused content, or C) a multifarious combination of the three.

In all, while this study relied on a non-representative (albeit a quota sample that ensures the participants resemble the overall population of teachers in the United States), post hoc assessment of teachers' experiences with professional development programs related to data driven decision-making, the conclusions can nonetheless still lead to benefits via the literature, teacher practice, and administrator practice, resulting in enhanced skills of teacher development. By utilizing a method that relied on enhanced computational power and a more nuanced understanding of mathematics and statistical inference, this dissertation helps professional development providers know that embedding collaborative learning elements, regardless of type (i.e. teamwork, generalized collaboration, shared knowledge building, etc.), in professional development experiences lead to an effective conveyance of knowledge related to data use in the classroom.

### **Recommendations for Future Research**

This research demonstrated that focused content and active learning may interact in interesting ways with collaborative learning. Future research ought to delve into that further to discern the nature of those relationships. As previously mentioned in the limitations section, an

experimental design could explain the conditions under which those relationships strengthen or degrade. For example, teachers who are interested in a data use professional development program could be randomly assigned to one of several conditions: 1) purely collaborative, 2) purely content focused, 3) purely active learning, 4) collaborative and content focused, 5) collaborative and active learning, 6) content focused and active learning, and 7) a control group that does not receive any professional development. The instruction would largely remain the same in each condition (except for the control group), and the other control variables would be held constant across the groups (i.e. all experiences should be the same in duration, coherence, etc.). Following completion of the programs, participants could either self-report their ability to use student data, or more ideally, a trained observer could score all participants in their actual quality of use of student data in the classroom to make instructional decisions. A simple one-way ANOVA and follow-up pairwise comparisons could then be conducted. Hopefully, that design would allow a researcher or professional development designer to understand what type or combinations of types in an experience would produce the best result. Obviously, this design would be quite expensive, and would require some significant work; however, it would quantitatively demonstrate the best combination of active learning, content focus, and collaboration by which to design a data use professional development program.

Another study that would push our knowledge of professional development forward could rely on manipulation of the quantity of collaborative learning to understand how much collaboration is needed for teachers to develop data use skills. Again, teachers could be randomly assigned to conditions with varied levels of collaboration, focused content, and active learning. For example, one condition could be an experience that is 100% collaborative, but only 25% focused on data use content; another condition could be that 50% of the learning is done

collaboratively, but 100% of the experience is focused on data use content. The dependent variable would be the same in this study possibility as the study design just discussed. Post hoc pairwise comparisons could demonstrate which combinations produce the best product.

This dissertation sought to empirically show a link between collaboration and classroom data use in sequence via self-efficacy and positive affect. Even though this relationship was conditionally demonstrated (depending on if the analysis employed control variables), it is probable other mediated pathways exist that connect collaborative learning with classroom data use. Discovering as many mediators as possible will aid in the generation of professional development design; it allows providers to embed elements that trigger those pathways. Thus, a future study may again draw on the survey method of data collection, asking questions that measure other psychological concepts, like motivation, personality traits, etc.

Finally, a less costly study could analyze these relationships from a qualitative perspective. A researcher could conduct in-depth interviews with teachers who have 1) recently completed data use professional development experiences, or 2) are currently engaged in a formal or informal experience. Pointed questions related to three of the five hallmarks of effective professional development (collaboration, active learning, and focused content) could help the researcher learn what teachers believe is working and what is not working in their attainment of classroom data use skills. That knowledge could help professional development providers or even professional learning community leaders know what to embed into the experiences.

## **Implications**

The conclusions made in this dissertation have several implications regarding data use professional development experiences as they relate to teachers and their acquisition of data use

knowledge. Specifically, this study contributes to our understanding of professional development as it pertains to data use in the classroom in three different areas: 1) to the social scientific literature, 2) to teacher practice, and 3) to administrator practice.

First, the literature is enhanced due to the study's ability to detail the mechanisms that explain the link between collaborative professional development and successful use of data in the classroom – something of which the extant research had yet to demonstrate empirically. Second, as has been detailed time and again, research has indicated that when teachers are able to successfully exhibit data literacy skills as part of their classroom practice, students are the beneficiaries in terms of their knowledge acquisition (Dunn, Airola, Lo, & Garrison, 2012; Edmonds, 1979; Evans, 2009; Fuller & Johnson, 2001; Mandinach & Gummer, 2016; Scheurich & Skrla, 2003; Stringfield, 1994; Wayman, Midgley, & Stringfield, 2006; Weber, 1971). In short, it is prudent that research reveals the factors that contribute to and facilitate this type of knowledge generation within teachers so they can implement this important skillset. Finally, administrators can be aided by this research, as it provides a roadmap, albeit one that may be incomplete, for the types of professional development programs school leaders ought to direct their teachers towards that maximize learning and successful behavioral adoption.

Another important implication of this study is its application to the design of professional development experiences. Professional development can take many forms – it can be a lecture, a demonstration, an action research project, or a professional learning community session (or sessions), among others. Given the open-ended nature of professional development, it may seem daunting for providers, teacher leaders, or administrators to create a data use experience or cumulative set of experiences that make best use of whatever instructional modality is being considered. This research has demonstrated that regardless of the type of professional

development a teacher experienced, as long as sufficiently high levels of collaborative learning were featured, teachers benefitted from the experience (by way of self-efficacy and positive affect in sequence or in parallel). Therefore, this provides additional evidence that collaboration is an essential element of professional development, even professional development geared towards student data use. Professional development designers should use this knowledge to create the most efficacious experience for teachers, especially if those experiences pertain to learning about using student data to make classroom decisions.

There are also theoretical implications to this dissertation research. Recall that Johnson and Johnson's (2009) theory of collaboration posited a pathway linking collaboration to cognition, which in turn links to affect, which causes an increased likelihood of successful outcomes. Their theory, though, did not stipulate what specific types of cognition and affect best facilitate that route. This research provided empirical support for their theory; moreover, the data demonstrated that a specific type of a cognitive structure (self-efficacy) and a specific type of affect (positive affect) may be the drivers of Johnson and Johnson's (2009) broad theory. In other words, this research tested a more precise version of the collaboration theory posited by Johnson and Johnson (2009). That is, this study demonstrated their broad theory can be applied to a specific factor (collaborative learning in a professional development experience), to a specific cognition type (data use self-efficacy), to a specific form of affect (data use positive affect), and finally, to a specific type of success (successful use of classroom data).

In sum, teachers of all grade levels and specialties ought to be adept data analysts in order to provide individualized instruction to students who need additional assistance to meeting state-mandated standards. By the same token, a teacher who is data literate will also be more likely to identify and provide enrichment opportunities to students who are excelling at various levels of



the learning cycle (Mandinach & Gummer, 2017). Developing data driven decision-making skills in service to classroom teaching is important; this dissertation hopefully helps elucidate the psychological pathways linking collaborative learning within a data use professional development experience and successful use of classroom data by teachers.

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## Appendix 1: Survey

### Data Use PD Experience

I. In the past 3 years, have you ever engaged in a teacher professional learning experience where the concept of data use in the classroom was discussed?

- A) Yes
- B) No

II. For what you deem to have been the most effective (or only) professional learning experience that discussed data use in the classroom over the past 3 years, what percentage of the time was dedicated to the topic of data use in the classroom?

Open Ended, constrained between 0 and 100

III. Still thinking about the most effective (or only) professional learning experience that discussed data use in the classroom over the past 3 years, about how many hours total did you spend exploring the topic of data use in the classroom?

Open Ended, constrained between 0 and 200

### Content Focused (Only displayed to teachers who answered “Yes” in the first question)

IV. Please indicate the degree of emphasis your most memorable data use professional development experience gave to deepening your content knowledge in using data in the classroom to aid your teaching.

1 = No Emphasis, 2 = Minor Emphasis, 3 = Moderate Emphasis, 4 = Major Emphasis

### Active Learning (Only displayed to teachers who answered “Yes” in the first question)

V. Please indicate the degree to which following statements described your most memorable data use professional development experience:

1. I received coaching and mentoring
2. I was observed by other teachers and received feedback
3. I was observed by the professional development leader or leaders and received feedback
4. I met with other participants to discuss classroom implementation
5. I reviewed student work
6. I conducted a lecture, presentation, or demonstration

Very Much Describes My Experience \_\_\_\_\_ Does Not Describe My Experience at All

### Coherence (Only displayed to teachers who answered “Yes” in the first question)

VI. Please indicate the degree to which you agree with the following questions related to your data use professional development experience:

1. This experience was consistent with my professional goals
2. This experience built upon what I learned in previous professional development experiences
3. This experience included activities that built upon what I learned

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

**Collective Participation (Only displayed to teachers who answered “Yes” in the first question)**

VII. Please indicate the degree to which you agree with the following questions related to your data use professional development experience:

1. This professional development experience was designed for all teachers in any school
2. This professional development experience was designed for teachers in my department
3. This professional development experience was designed for teachers in my grade level

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

**Trait Collaboration and Collaboration Enjoyment**

VIII. Please indicate your level of agreement with the following statements:

1. I behave collaboratively with others frequently in my professional life
2. I behave collaboratively with others frequently in my personal life
3. I find that I do not enjoy collaborating with other teachers professionally
4. I find that I do not enjoy collaborative experiences in general

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

**Teamwork (Only displayed to teachers who answered “Yes” in the first question)**

IX. Please indicate to what degree your most memorable data use professional development experience was comparable to the following statements.

1. We did not work well as part of a team
2. When problems arose, everyone in my team worked together to solve them
3. The team I primarily worked with was not continually assessing its progress
4. The team I primarily worked with regularly discussed ways to improve our performance

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

**Shared Knowledge Building (Only displayed to teachers who answered “Yes” in the first question)**

X. Please indicate to what degree your most memorable data use professional development experience was comparable to the following statements.

1. My views and knowledge broadened through working with others
2. Ideas from different members were not synthesized into new knowledge
3. Ideas from different professional development members were equally valuable
4. Goal setting and planning for our progress was not important
5. We exchanged our ideas to improve our knowledge
6. The knowledge we worked on together was not relevant to our real classrooms

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

**Generalized Collaboration (Only displayed to teachers who answered “Yes” in the first question)**

XI. Still thinking about the same professional learning experience related to data use in the classroom, please indicate to what degree your most memorable data use professional development experience was comparable to the following statements.

1. I felt part of a learning community
2. I actively exchanged my ideas with fellow participants
3. I was not able to develop new skills and knowledge from other participants
4. I was not able to develop problem solving skills through peer collaboration
5. Collaborative learning amongst my fellow participants was not effective
6. Collaborative learning amongst my fellow participants was time-consuming
7. Overall, I am satisfied with the collaborative nature of my learning

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

**Data Self-Efficacy**

XII. Please indicate how much the following statements describe you.

1. I am not confident in my ability to access state assessment results for my students
2. I am confident that I know what types of data or reports I need to assess group performance

3. I am not confident that I know what types of data or reports I need to assess student performance
4. I am confident I can use the tools provided by my district's data technology system to retrieve charts, tables, or graphs for analysis
5. I am not confident I can use the tools provided by my district's data technology system to filter students into different groups for analysis
6. I am confident that I can use my district's data analysis technology to access standard reports
7. I am not confident in my ability to understand assessment reports
8. I am confident in my ability to interpret student performance from a scaled score
9. I am not confident in my ability to interpret subtest or strand scores to determine student strengths
10. I am confident that I can use data to identify students with special learning needs
11. I am not confident that I can use data to identify gaps in student understanding of curricular concepts
12. I am confident that I can use assessment data to provide targeted feedback to students about their performance or progress
13. I am not confident I can use assessment data to identify gaps in my instructional curriculum
14. I am confident that I can use data to group students with similar learning needs for instruction
15. I am confident in my ability to use data to guide my selection of targeted interventions for gaps in student understanding
16. I am intimidated by statistics
17. I am intimidated by the task of interpreting students' state level standardized assessments
18. I am concerned that I will feel or look dumb when it comes to data driven decision-making
19. I am intimidated by my district's' data retrieval technology
20. I am intimidated by the process of connecting data analysis to my instructional practice

Very Much Describes Me \_ \_ \_ \_ \_ Does Not Describe Me at All

### **Positive and Negative Affect**

XIII. Please indicate to what degree you agree with the following statement: "When I think about using data in the classroom, I believe I experience the following feelings:"

1. Cheerful
2. Healthy
3. Satisfied
4. Enjoyment
5. Interested
6. Happy
7. Confident
8. Friendly
9. Energetic

10. Relaxed
11. Tense
12. Afraid
13. Dissatisfied
14. Sad
15. Worried
16. Hostile
17. Nervous
18. Irritated
19. Angry
20. Depressed
21. Upset

1 = Strongly Disagree, 2 = Disagree, 3 = Slightly Disagree, 4 = Neither Disagree nor Agree, 5 = Slightly Agree, 6 = Agree, 7 = Strongly Agree

**Data Use in the Classroom 1 (Addresses Frequency, Duration, and Intensity)**

XIV. How frequently do you use data in the classroom as part of your teaching practice?

- A) Haven't used
- B) Once a year
- C) Once every six months
- D) Once every three months
- E) Once a month
- F) Once a week
- G) Once every 4-5 days
- H) Once every 2-3 days
- I) Once a day

XV. What percentage of your planning and teaching time is designated to analyzing student data to inform your teaching?

(Open ended, constrained by numbers, ranging between 0% and 100%)

XVI. How intently do you analyze student data to aid in your decision-making processes related to your classroom and teaching?

Intently \_ \_ \_ \_ \_ Casually

**Data Use in the Classroom 2**

XVII. Please indicate your level of agreement with the following statements:

1. I think I successfully access state assessment results for my students
2. I think I unsuccessfully use different types of data or reports I need to assess group performance

3. I think I successfully use different types of data or reports I need to assess student performance
4. I think I unsuccessfully use the tools provided by my district's data technology system to retrieve charts, tables, or graphs for analysis
5. I think I successfully use the tools provided by my district's data technology system to filter students into different groups for analysis
6. I think I competently use my district's data analysis technology to access standard reports
7. I think I incompetently use data to identify students with special learning needs
8. I think I competently use data to identify gaps in student understanding of curricular concepts
9. I think I incompetently use assessment data to provide targeted feedback to students about their performance or progress
10. I think I effectively use assessment data to identify gaps in my instructional curriculum
11. I think I ineffectively use data to group students with similar learning needs for instruction
12. I think I effectively use data to guide my selection of targeted interventions for gaps in student understanding

1 = Strongly Disagree, 2 = Disagree, 3 = Neither Disagree nor Agree, 4 = Agree, 5 = Strongly Agree

### **Data Use in the Classroom 3**

XVIII. Please indicate to what degree the following two statements describe you.

How would you rate your use of student data to aid your classroom instruction and make decisions?

Strong \_\_\_\_\_ Weak

How would you rate your district's student data retrieval system?

Lacking \_\_\_\_\_ Excellent

### **Demographics and Similar Questions**

XIX. Please indicate the level of support you think you receive from your school leaders in order for you to learn and practice student data to inform your practice:

I Feel Very Unsupported \_\_\_\_\_ I Feel Very Supported

XX. What best describes your role as an educator?

1. Teacher
2. Administrator

XXI. What is your employment status as an educator?

1. Full-time
2. Part-time
3. Not currently a practicing teacher

XXII. How old are you?

(Open-ended, ranges from 21-90)

XXIII. About how many years have you been teaching?

(Open-ended, ranges from 0-80)

XXIV. What is your gender?

1. Male
2. Female

XXV. At what type of school do you currently work?

1. Public
2. Private
3. Other

XXVI. What grade level do you currently teach, or if you're not currently a teacher, what grade level have you most recently taught?

1. K/Pre-K
2. 1<sup>st</sup>
3. 2<sup>nd</sup>
4. 3<sup>rd</sup>
5. 4<sup>th</sup>
6. 5<sup>th</sup>
7. 6<sup>th</sup>
8. 7<sup>th</sup>
9. 8<sup>th</sup>
10. 9<sup>th</sup>
11. 10<sup>th</sup>
12. 11<sup>th</sup>
13. 12<sup>th</sup>

XXVII. In what subject areas do you currently teach or specialize, or if you're not currently a teacher, in what subject areas have you most recently taught? If your area is not represented, please select the area that might best describe your subject.

1. Social studies / history / geography

2. Science
3. English / Language arts
4. Math
5. Arts
6. Special education
7. General education
8. Other

XXVIII. This is a COMPLETELY optional question. I know this survey was long (sorry...), but do you have anything you'd like to share with me about your classroom data use experiences?



## Appendix 2

### Qualitative Responses to the Open-Ended Survey Questions

Note: Responses were edited for grammar and clarity, when appropriate

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Male: 20-29

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Data driven instruction is logically terrific.

I've had many in five years. They always throw them at us.

My district has adopted Mastery Connect as a way to track student progress within standards. I appreciate the idea of it, but find it poorly implemented, especially for the cost of the program. One of my big frustrations I have found is that not all teachers are assessing in a uniform way, so the data itself is skewed or misleading. With NGSS, my district has moved towards using less multiple-choice questions and using more writing responses to prove mastery over a specific learning objective, which leads to stark differences between 'harsh graders' and 'easy graders.' As frustrating as standardized testing can be, at least it is standardized.

TFA has pushed me more to utilize data driven instruction than KCPS has.

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Male:30-39

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It helps if administrators understand its usage. One principal was hostile toward it and discouraged other teachers from using the information.

It's really got the students in mind.

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Male: 40-49

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Data does help more than most people think.

Data is too broad and too much time is spent in convoluted collection methods that turn students off, leading to less than honest assessments of understanding and or mastery.

Our data system is garbage, I can get math and reading scores from two years ago but that's about it. We have over 15% transiency per year so many of our students don't even have that info. The biggest barrier is time, even if I had the data and felt it was relevant, I don't have the time to add data analysis into my planning. Since I have literally seen kids fall asleep and deliberately include incorrect and joke answers in their MAP tests there is no point in even trying to make the time to include it, and I don't have the time to track and compile assessment data from my own assessments.

PD at the high school level is too data driven. It's like analytics in baseball, it can only get you so far. At some point, you just need to be able to get through with your ideas and the students need to know you care about them. That's the most important PD right there. Data does not enhance classroom teachers. Core values and administrators that can actually handle and control a school environment are the most important pieces for education.

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Male: 50+

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It is getting to be a waste of time we desperately need to put elsewhere.

My district has changed assessment software and looked at different types of data very frequently (at least yearly). Each new superintendent and/or building principal has changed what data they want the teachers to focus on (e.g. state assessments, district assessments, behavioral data, demographic data). Teachers are never sure what is supposed to be important at the building and district levels, so they focus on the assessment data they collect in their classrooms because it is more reliable. Teachers are also reluctant to share their classroom data for fear that they are doing something wrong or not doing enough.

Not a lot of data is available for journalism classes. That was my teaching area. I did teach English classes, but with the focus on math/science, little data at the time I was teaching targeted high school reading, interpretation of literature, and the teaching of writing. Also, use and teaching of grammar has been eliminated from curriculum. Using data to assess language arts curriculum was basically limited to a few state assessments, most of which provided useless data for teachers and students.

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Female: 20-29

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I am a gifted resource teacher and really don't have access to my students' data.

I am confident with the systems/gathering data, but would like to spend more time (or possibly training) in effectively using the data for grouping & instructional targeting practices.

I serve at an alternative school that provides services to students with EBD and students with autism. Smaller districts with smaller special education programs cannot support these students, so we serve them.

I wish it was easier to interpret.

Our principal is very much into data and we consistently analyze data after formal assessments. It is exceptionally important for us when we take district tests to see where we rank compared to other schools.

The organization that funds Pre-K in my community emphasizes the use of data very heavily, so Pre-K teachers here are very familiar with using data to "drive instruction."

There doesn't seem to be enough time in the day to use data the way it could be used.

We track student data weekly, and group changes can occur based on those results. As a school we assess data during PD monthly (if not more). We have built-in intervention time to our schedule to help struggling students. Weekly data is looked at by each teacher, grade level, manager and principal.

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Female: 30-39

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Data Driven instruction is a big buzz-word that administrators like to toss around, but they rarely have concrete ways the data can impact student performance.

I am still learning how to incorporate data into my classroom.

I feel that my district is great at emphasizing data and how to interpret it. When I started teaching, this was one area that I knew nothing about straight out of college. I have learned a lot about this working with colleagues from various subject areas and attending professional development opportunities. I also am thankful that my school makes all subject areas feel included in these trainings, even those of us in Health and PE.

I wish we had more training on how to use and apply data to benefit our instruction.

Our data is not traditional state testing due to special education.

Social workers and other related service providers don't always benefit from data PD. And staff are not always understanding related service providers' data.

Yes. I think the use of data and making formative assessments was something they pushed really hard a couple of years ago but have now completely backed off on. It'd be nice to have some ongoing professional development on how to develop your informal assessments.

Female: 40-49

a lot of talk and no action is the way it goes.

Educational and effective.

Great topics.

I am a math recovery intervention specialist so I use progress monitoring data on a daily basis.

I am a school psychologist which I think may give a different impression since all our work is data driven and teaching/supporting staff.

I teach writing classes to seniors, so much of my "data" consists of student essays and short responses. As such, I feel confident in my ability to "read" my students' needs. I have some data on their reading ability, so anyone who is in the lowest rungs gets some discussion of how to deal with difficult texts. But my feedback is individual to students every time, at least once a week. This explains why I burned out and I'm part-time right now.

I work in an ASD classroom. Our goal is to get kids into general education ASAP.

Incorporating data is hard and I second guess myself daily due to the pressures placed on data analysis to judge students. Students are more than a test score.

It is very time consuming to gather PD data.

Only had one undergrad statistics course, needed more!

State results are given after students have moved onto the next grade. This makes the scores irrelevant except to the teacher on what to teach better. Incoming student results are not given to the new teacher.

The problem with PD is teachers getting blamed when in reality it's the family structure that is falling apart. It makes it difficult to make progress with student when it expected to all be done at school.

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Female: 50+

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A lot is not worth the time that we put into it.

Discrepancies between reports. Self-reported ethnicity impacts results by gap groups.

I do use data, but I teach study halls now, so not very much.

I think collaboration with colleagues is important.

I use data frequently in my class.

It has been very helpful getting this training.

It seems that educators are forced to rely on data in ways which we are not trained to do.

It's helpful.

It's kind of trying.

My kids love the data things we do in classroom.

Please use your research to improve PD.

Since my retirement, I hope there has been more professional development for elementary teachers on how to use all the amazing statistics that are available to help individualize instruction for children!

Sometimes too much emphasis is put on data and not looking at the child as a whole. We have to think about what was going on in a child's life when taking the data.

The use of data isn't as much about the PD event as the actual doing it. Once you know, then you do it as long as the expectation to use it is there and the schedule makes it a priority. As I was completing this survey I was using my frame of reference for my data use PD as my grade level's year-long work with data teams and using the information from our scores to continue to plan next steps for instruction. That may not fit with what you had envisioned as DUPD.

The use of data was overwhelming at first, but now that we are a few years into it is much easier.

We are increasingly asked to provide reports using data, and this always feels incredibly negative. I believe that using data to inform instruction could and should be positive and useful in promoting student learning; however, this is not always my experience at school.

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